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Creation of Hot Summer Years and Evaluation of Overheating Risk at a High Spatial Resolution under a Changing Climate

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Creation of Hot Summer Years and Evaluation of Overheating Risk at a High Spatial Resolution under a Changing Climate

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Abstract

It is believed that the extremely hot European summer in 2003, where tens of thousands died in buildings, will become the norm by the 2040s, and hence there is the urgent need to accurately assess the risk that buildings pose. Thermal simulations based on warmer than typical years will be key to this. Unfortunately, the existing warmer than typical years, such as probabilistic Design Summer Years (pDSYs) are not robust measures due to their simple selection method, and can even be cooler than typical years. This study developed two new summer reference years: one (pHSY-1) is suitable for assessing the occurrence and severity of overheating while the other (pHSY-2) is appropriate for evaluating the thermal stress. Both have been proven to be more robust than the pDSYs. In addition, this study investigated the spatial variation in overheating driven by variability in building characteristics and the local environment. This variation had been ignored by previous studies, as most of them either created thermal models using building archetypes with little or no concern about the influence of local shading, or assumed little variation in climate across a landscape. For the first time, approximately a thousand more accurate thermal models were created for a UK city based on the remote measurement including building characteristics and their local shading. By producing overheating and mortality maps this study found that spatial variation in the risk of overheating was considerably higher due to the variability of vernacular forms, contexts and climates than previously thought, and that the heat-related mortality will be tripled by the 2050s if no building and human thermal adaptations are taken. Such maps would be useful to Governments when making cost-effective adaptation strategies against a warming climate.

Main outputs

During this PhD study the following was achieved:

- two approaches to the creation of new summer reference years, which include hot summer weather data, for the study of overheating and human thermal comfort in buildings now and under a possible future climate;
- a study of spatial variation in overheating across a UK city using these weather files;
- the measurement of approximately a thousand real buildings in the city using a remote surveying tool;
- the creation of more accurate building models based on the remotely measured building information that included dwelling types, orientations, local shadings, wall dimensions, wall types, window dimensions, window types, glazing types, glazing ratios, opening types and opening ratios;
- in total, 90,700 dynamic thermal simulations (each of 907 unique thermal model has been simulated with the 1st to 100th percentile HSYs) for now and a future warming climate respectively;
- the production of overheating risk maps at a grid resolution of 5 km for this city based on buildings found in each grid area and housing stock statistics in each grid area;
- the production of heat-related mortality maps at a fine spatial resolution for now and in the future considering the effect of human thermal adaptation.

The following journal papers were published during the PhD study:

- **Liu, C.**, Kershaw, T., Eames, M.E. and Coley, D.A., 2016. Future probabilistic hot summer years for overheating risk assessments. Building and Environment, 105, pp. 56-68;
- **Liu, C.**, 2016. Future weather dataset for fourteen UK sites. Data in Brief, 8, pp. 1308-1310;
- **Liu, C.**, Kershaw, T., Fosas, D., Ramallo Gonzalez, A.P., Natarajan, S. and Coley, D., 2017 High resolution mapping of overheating and mortality. Building and Environment, 112, pp. 1-14;
- Coley, D., Herrera, M., Fosas, D., **Liu, C.** and Vellei, M. 2017. Probabilistic adaptive thermal comfort. Building and Environment, 123, pp. 109-118.

The following conference papers were presented during the PhD study.

- **Liu, C.** and Coley, D., 2015. Overheating Risk of UK Dwellings under a Changing Climate. Energy Procedia, 78, pp. 2796-2801 (oral presentation);
- **Liu, C.** and Coley, D., 2015. Development of Future Probabilistic Hot Summer Years for Overheating Risk Assessment in the UK. In: 14th Conference of International Building Performance Simulation Association, BS 2015, Hyderabad, India, 7th to 9th December 2015. pp. 1024-1031 (oral presentation);
- **Liu, C.** and Coley, D., 2016. Spatial variations in overheating risk of dwellings under a changing climate: a case study of Sheffield, UK. In: 32nd Conference on Passive and Low Energy Architecture: Cities, Buildings, People: Towards Regenerative Environments, PLEA 2016, Los Angeles, USA, 11th to 13th July 2016. pp. 429-437 (oral presentation);
- Herrera, M., Eames, M., Ramallo Gonzalez, A., **Liu, C.** and Coley, D., 2016. Quantile regression ensemble for summer temperatures time series and its impact on built environment studies. In: International Congress on Environmental Modelling and Software, 10th to 14th July 2016, École nationale supérieure d'électronique, d'électrotechnique, d'informatique, d'hydraulique et des télécommunications.

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I would not be the person I am today without my forever beloved family. I would like to thank my family for their endless love and great dedication in the successful completion of my PhD study.

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List of Acronyms

ADHC	Accumulated Degree Hours over Comfort temperature
ANSI	American National Standards Institute
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BADC	British Atmospheric Data Centre
BEPAC	Building Environmental Performance Analysis Club
BLAST	Building Loads Analysis and System Thermodynamics
BRE	Building Research Establishment
BREDEM	BRE Domestic Energy Model
BS EN	UK version in English of a European harmonised standard
CCWeatherGen	Climate Change Weather file Generator
CDF	Cumulative Distribution Function
CDH	Cooling Degree Hour
CFD	Computational Fluid Dynamics
CHM	Cambridge Housing Model
CIBSE	Chartered Institution of Building Services Engineers
CMIP3	Phase 3 of the Coupled Model Inter-comparison Project
CMIP5	Phase 5 of the Coupled Model Inter-comparison Project
DCLG	Department for Communities and Local Government
DOE	Department of Energy
DRY	Design Reference Year
DryT	Dry bulb temperature
DSY	Design Summer Year
EFUS	Energy Follow Up Survey
EHS	English Housing Survey
EPC	Energy Performance Certificate
EPW	EnergyPlus Weather file
ESP-r	Environmental Systems Performance, Research version
ESRU	Energy Systems Research Unit
EST	Energy Saving Trust
EWY	Example Weather Year
FS statistic	Finkelstein-Schafer statistic
GCMs	Global Climate Models
GIRad	Global solar horizontal irradiation
GIS	Geographic Information System
HDH	Heating Degree Hour
HEED	Home Energy Efficiency Database
HVAC	Heating, Ventilation and Air Conditioning

IDF	Input Data File
IES<VE>	Integrated Environmental Solutions <Virtual Environment>
IPCC	Intergovernmental Panel on Climate Change
IPCC AR4	IPCC Fourth Assessment Report
IPCC AR5	IPCC Fifth Assessment Report
ISD	Integrated Surface Database
IWEC	International Weather Years for Energy Calculations
LSSAT	London Site Specific Air Temperature
MEMI	Munich Energy balance Model for Individuals
MME	Multi-Model Ensemble
MORUSES	Met Office–Reading Urban Surface Exchange Scheme
NEED	National Energy Efficiency Data-Framework
NREL	National Renewable Energy Laboratory
PDF	Probability Distribution Function
pDSY	probabilistic Design Summer Year
pDSY	probabilistic Design Summer Year
pDSY-1	probabilistic Design Summer Year No.1
pDSY-2	probabilistic Design Summer Year No.2
pDSY-3	probabilistic Design Summer Year No.3
PET	Physiologically Equivalent Temperature
PHI	Passive House Institute
PHPP	Passive House Planning Package
pHSY-1	probabilistic Hot Summer Year No.1
pHSY-2	probabilistic Hot Summer Year No.2
pHSYs	probabilistic Hot Summer Years
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
PPE	Perturbed Physics Ensemble
pTRY	probabilistic Test Reference Year
RCMs	Regional Climate Models
RCP	Representative Concentration Pathway
RdSAP	Reduced data SAP
SAP	Standard Assessment Procedure
SET	Standard Effective Temperature
SRES	Special Report on Emission Scenarios
SRY	Summer Reference Years
SWCDH	Static Weighted Cooling Degree Hours
TMY	Typical Meteorological Year
TMY2	Second edition of TMY
TMY3	The latest edition of TMY
TRY	Test Reference Year

TWCDH	Threshold Weighting Degree Hours
UHI	Urban Heat Island
UKCIP02	UK Climate Impacts Programme 2002
UKCP09	UK Climate Projections 2009
UKCP09 WG	UKCP09 Weather Generator
UMY	Untypical Meteorological Years
UNFCCC	United Nations Framework Convention on Climate Change
WCDH	Weighted Cooling Degree Hours
WRY	Warm Reference Year
WS	Wind Speed
WYEC	Weather Years for Energy Calculations
WYEC2	WYEC version 2
XMY	eXtreme Meteorological Year

1. Introduction

1.1. Research background

The European heatwave in August 2003 caused 52,000 excess deaths (Larsen, 2006b). One of the main reasons was that buildings failed to protect people, in particular the elderly people who were more likely to stay at home, against such hot spells (Vandentorren *et al.*, 2006). Due to the changing climate, the frequency and intensity of such hot events are projected to increase in the future (IPCC, 2013), and the hot summer in 2003 is likely to become a typical summer by the 2040s (Stott *et al.*, 2004). In such a warming world we will face a challenging risk in the future. For instance, the annual heat-related deaths are likely to increase to more than triple by the 2050s (Stott *et al.*, 2004); there will be a significant increase in the risk of overheating in the future (Gupta and Gregg, 2013; Gupta and Gregg, 2012; Kershaw *et al.*, 2011; Jentsch *et al.*, 2008; Gul *et al.*, 2012; Demanuele *et al.*, 2012; McLeod *et al.*, 2013; Patidar *et al.*, 2011; Taylor *et al.*, 2014; Jenkins *et al.*, 2014); moreover, the overheating risk by the 2080s is unlikely to be eliminated completely by passive adaptations, e.g. opening window, installing shading devices and solar reflective coating on external walls (Tillson *et al.*, 2013; Gupta and Gregg, 2012). Those studies were based on dynamic thermal simulation with summer reference years, i.e. warmer than typical years, which has become an important exercise for building practitioners. However, it was found that there were critical issues with the existing summer reference years. Though researchers (Eames *et al.*, 2011; Smith and Hanby, 2012; Watkins *et al.*, 2012; Jentsch *et al.*, 2015; Ji *et al.*, 2016) have made efforts to address the issues, none of them could successfully provide robust summer reference years. Hence, this study aimed to develop new summer reference years for use in the assessment of overheating and thermal discomfort.

Thermal failures in buildings are driven by not only thermal characteristics of buildings but also the local environment, i.e. context and weather. Neither thermal characteristics of buildings nor their local environment are uniform across a landscape, leading to the hypothesis that there would be a considerable spatial variation in overheating. Unfortunately, this variation has been paid little attention by previous studies (Mavrogianni *et al.*, 2012; Oikonomou *et al.*, 2012; Taylor *et al.*, 2014; Gupta and Gregg, 2012; Gupta and Gregg, 2013) which either created thermal models using building archetypes with little or no concern about the influence of local shadings, or assumed little variation in climate over a large area. In the UK, the UKCP09 Weather Generator (UKCP09 WG) (Jones *et al.*, 2010) can provide both current and future weather data set at a 5km by 5km horizontal resolution so that the spatial variation in climate can be measured. However, the building characteristics and local shading at such a high spatial resolution were unavailable for dynamic thermal modelling. The investigation into the spatial variation in the risk of overheating and heat-related mortality will be more convincing if the dynamic thermal models are created based on the measurement of real dwellings and their local environment as they are key to the indoor thermal comfort analysis. This study aimed to create more realistic thermal models, for the first time, based on the measurement on a number of dwellings and their surrounding obstructions found in each 5km by 5km grid area of a UK city. Then the relative impact of variability in dwellings and weather on spatial variation in overheating were discussed. In addition, an innovative approach to map the risk of overheating and its associated mortality at a high spatial resolution for now and in the future was proposed. The maps might be beneficial to the health or housing policy makers to identify the areas of great concern and provide appropriate and sustainable adaptations.

1.2. Scope of the research

UK dwellings are predominantly naturally ventilated buildings; therefore, their respond to the external weather is critical to the indoor thermal environment. Due to the warming climate, the concern over the risk of overheating has been on the rise as it could lead to fatal health problems.

In order to test whether or not buildings are able to provide a safe and comfortable indoor environment against global warming, appropriate future summer reference years are essential. The CIBSE has released current and future TRYs and DSYs for fourteen UK sites. In fact, the methods used to create current TRYs and DSYs have been largely maintained in the future TRYs and DSYs creation until the commencement of this study. The TRY method has been widely accepted while the simple DSY selection method has been critiqued. The three main issues with the DSY are: (1) overheating risk predicted from the DSY (i.e. warmer than the typical year) was not consistently higher than that from the TRY (i.e. the typical year); (2) the DSY is not suitable for measuring the severity of overheating; (3) a single weather variable (i.e. mean dry bulb temperature) was considered when creating DSY (Jentsch *et al.*, 2013).

This study aimed to develop alternative approaches to creating future probabilistic Hot Summer Years (pHSY), i.e. new summer reference years. They were produced for the same fourteen sites as the CIBSE TRYs/DSYs provided for the purpose of comparison between new and old selection methods. The new approach is intended to overcome the three main issues with the simple DSY selection method as listed above. There are variations in thermal characteristics of buildings which may result in substantial variations in thermal responses to the external weather. Thus, it is hard to consider all building types when developing new summer reference years. In order to make progress with the summer reference years, CIBSE TM49 (CIBSE, 2014) proposed a reference conceptual building to represent a building with a very high natural ventilation rate. This conceptual building has been used in this study to test the robustness of pHSYs for fourteen UK sites.

Realistic thermal models are as important as summer reference years for the convincing assessment of overheating risk. Neither dwelling characteristics nor weather are uniform across a landscape. This study aimed to take account of the variability of the dwelling characteristics, context and weather conditions when investigating the spatial variation in overheating for a UK city. The current and future pHSYs (i.e. from the 1st to 100th probabilistic HSYs for the 2020s and 2050s) were produced at a 5km by 5km grid resolution for the city which showed a great topographic variation. For the first time, a remote surveying tool was used to measure a great number of dwellings and their local environments found in each grid square of 5km by 5km over the city. Then, more accurate and realistic dynamic thermal models of real buildings were created for the studying of the spatial variation in overheating. Maps of overheating risk and its associated mortality rate were produced for the city. Though the spatial variability of overheating and heat-related mortality were investigated for one city, the methods proposed in this study are applicable worldwide.

1.3. Research aims and objectives

This research aimed to assess the risk of overheating and its associated mortality now and in the future at a high spatial resolution to identify the area of critical concern so that governments can make effective adaptation strategies against the warming climate. Appropriate current and future weather files and realistic thermal models are significantly important in this modelling based study. The following objectives have been developed in order to achieve the research aim:

- recognize the shortcoming of the existing summer reference years for use in study of overheating;
- propose new approaches to the creation of robust current and future summer reference years in order to overcome the main shortcomings of the previous methods;
- justify if the new summer reference years (pHSY-1 which were created based on WCDH) are suitable for measuring the duration as well as the severity of overheating;
- justify if the new summer reference years (pHSY-2 which were created based on the combined effects of all the thermally related weather variables rather than a single one) are appropriate for evaluating human thermal discomfort;
- investigate the robustness of the new future pHSYs in a reference conceptual building to determine whether or not the new pHSYs can consistently deliver longer overheating hours and more severe overheating risk than the typical years such as pTRYs;
- recognize the limitation in the existing modelling based overheating study due to the lack of measured building information at a large scale;
- explore the spatial variation in overheating risk due to the variability in dwelling characteristics, local shading and location (i.e. localised weather) based on approximately a thousand more realistic thermal models for a landscape with great topographic differences under different climate scenarios (e.g. high emission scenario in the 2020s and 2050s);
- analyse the relative impact of variability in the dwelling characteristics (including local shading effects) and localised weather years on the spatial variation in overheating;
- and map the risk of overheating and heat-related mortality to identify the areas with critical concern regarding severity of overheating, the population of overheated dwellings and the heat-related mortality under changing climates.

1.4. Outline of thesis

This thesis is comprised of six chapters plus appendices.

Chapter 2 (Literature review) introduces the research background including climate change and its impact on indoor thermal environment in the first place; then it reviews current approaches to thermal comfort analysis including the use of thermal comfort models, assessment criteria, thermal modelling for dwellings; afterwards, it reviews the approaches to the development of current and future summer reference years which were used to assess the risk of overheating in the naturally ventilated buildings; finally it discusses the limitations in previous research on overheating risk assessment under current and future climates.

Chapter 3 shows one of the main outputs from this research which has been published in the journal of Building and Environment. This chapter presents two alternative approaches to the creation of future pHSYs, as mentioned above, which can overcome the main issues with the existing methods.

Chapter 4 details the creation of realistic thermal models based on the remote measurement including real dwelling characteristics and local shading.

Chapter 5 presents another important contribution from this research which has also been published in the journal of Building and Environment. This chapter proposes an innovative method to investigate the spatial variation in the risk of overheating due to the variability in the dwelling characteristics, context and localised weather. The current and future pHSYs (the first main output of this research presented in chapter 3) have been produced at a high spatial resolution for a case study city with an apparent topographic variation. High resolution maps of severity of overheating, overheated dwellings, and heat-related mortality rate are illustrated in this chapter.

Chapter 6 restates the importance of this research, summarises the main work, highlights the research contributions, mentions the research limitations and suggests future work.

Appendices include details of thermal models, a statement of authorship of each published academic paper, and evidence of permission from the publisher to reuse full articles in this thesis.

2. Literature Review

2.1. Climate change

2.1.1. Climate change projections

Being distinguished from weather which describes meteorological parameters such as temperature, pressure, humidity, wind, clouds, precipitation etc. commonly for a location over a short period of time, climate usually refers to statistically analysed weather condition typically over a 30-year long period of time (IPCC, 2013). The Intergovernmental Panel on Climate Change (IPCC, 2007a) defines climate change as any change in climate for decades due to natural causes as well as the anthropogenic influence while the United Nations Framework Convention on Climate Change (UNFCCC) only considers climate change due to human activity (UN, 1992).

Climate is changing, for instance, land and sea surface temperatures are increasing and Arctic sea ice is shrinking due to the increasing greenhouse gas concentrations (IPCC, 2013). The rising land surface temperature is one of the key drivers for overheating so that the warming climate needs to be taken into account when assessing overheating risk in the future. According to the IPCC Fifth Assessment Report (IPCC AR5) global surface temperature is likely to increase 2.6°C to 4.8°C (for the RCP8.5 scenario) by the end of this century relative to the reference period of 1986 to 2005 (IPCC, 2013). RCP stands for Representative Concentration Pathway which is a new scenario used in climate change projection by the IPCC. There are four scenarios such as the RCP2.6, RCP4.5, RCP6.0 and RCP8.5 which take a range of 21st century climate policies into consideration. The RCP8.5 represents very high greenhouse gas emissions. More warm but fewer cold days and nights have been detected since 1950. Furthermore, the frequency and duration of heat wave have increased since the middle of the 20th century; and it is very likely that occurrence of such hot events will increase over most land areas by late 21st century (2081-2100) due to the human influence (IPCC, 2013).

2.1.2. Climate models

Based on the latest scientific understanding of climate science, scientists have set up climate models to understand the anthropogenic influence on the climate system and to predict future climate change based on different future emission scenarios. Climate models are numerical models which have been developed based upon the physical processes, i.e. atmospheric processes, ocean processes, terrestrial processes and cryospheric processes (Randall, 2007). The validated climate models are able to reproduce the past and current climates, and more importantly, predict future climate condition. Warming climate projected by climate models has been proven to be consistent with the observed climate change.

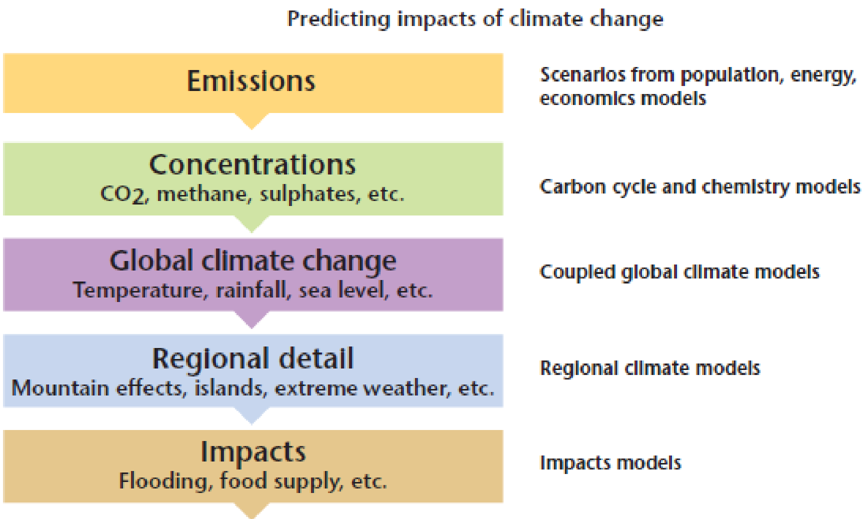


Figure 2-1. The main stages required to provide climate change scenarios for assessing the impacts of climate change (Jones, 2004).

The various climate models in the world can be classified into Global Climate Models (GCMs) and Regional Climate Models (RCMs). As illustrated in Figure 2-1, emission scenarios which were constructed based on the population growth, socio-economic development, etc., provide estimates of carbon concentrations in the future. GCMs have taken account of impacts of carbon concentrations on climate system to forecast the global climate change. The horizontal grid resolution of GCM (e.g. 300 km x 300 km grid square) is too coarse to understand the impact of a changing climate on human life and make an adaptation plan against it. Scientists have used two different (i.e. statistical and dynamic) approaches to downscale the GCMs outputs. The statistical method uses a long period of high quality observed data to set up statistical relationships between regional and global scale climate components and derives regional climate information from GCMs (Murphy, 2000). The downside of the statistical method is the uncertainty of the relationships which might change in the future (Jones, 2004). RCM is considered as a dynamic approach which is based on the physical processes like GCM. RCM uses GCM outputs as boundary inputs for the region of interest. Regional physiographic details are taken into the RCMs so that RCM outputs are more realistic than GCMs particularly in the regions with great topographic variations. Figure 2-2 shows the horizontal resolutions of GCM and RCM which show the distributions of winter precipitation across the UK. Finer horizontal grid resolution is available from RCMs which only consider atmosphere and land surface components of climate system with a much smaller scale. The UK Hadley Centre HadRM3 (i.e. RCM) can run at a horizontal grid resolution of 25 km as can be seen in Figure 2-2. Rainfall recorded by 4400 stations was spatially interpolated to produce gridded data sets at a higher horizontal resolution of, for instance, 5 km over the UK as shown in Figure 2-2 (Perry and Hollis, 2005). The outputs from the RCMs are more representative of the observation compared to GCM. The regional climate change projections, therefore, have been incorporated into the weather generators such as UKCP09 WG (Jones *et al.*, 2010) which has been used to construct localised future weather years for use in building simulations.

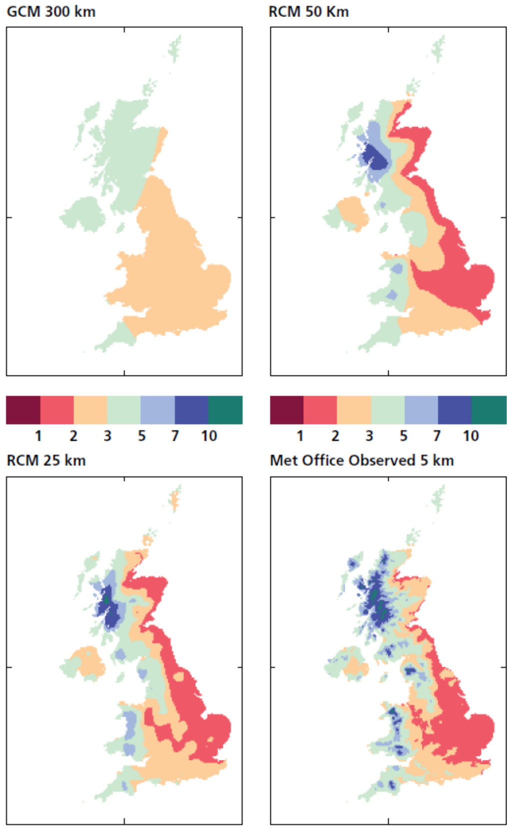


Figure 2-2. Average winter precipitation (mm/day) across the UK for 1961 to 2000 at different horizontal resolutions derived from Global Climate Models (HadCM3), Regional Climate Models (HadRM3) and observation. This image was originally from UK Met Office and was reproduced by Murphy et al. (2010).

None of the current climate models are perfect owing to the imperfect understanding of climate system, uncertainties in future emission and concentrations, and so on (Jones, 2004). Different climate models provide slightly different projections due to the uncertainties in climate modelling. Multi-Model Ensemble (MME) approach has been used to understand and quantify the uncertainties in climate change projections. MME includes more comprehensive understanding of climate science than the single climate model (Randall, 2007). The purpose of using ensembles of a number of different climate model simulations is to provide more credible climate change projections (IPCC, 2007b). The outputs of climate models developed by different countries have been archived to comprise the phase 3 of the Coupled Model Inter-comparison Project (CMIP3) of the World Climate Research Programme. The climate change projections from CMIP3 were included in the IPCC Fourth Assessment Report (AR4) (IPCC, 2007b). More advanced and more than twice number of climate models experiments constituted the phase 5 of the Coupled Model Inter-comparison Project (CMIP5). The climate projections from CMIP5 were included in the latest IPCC AR5 (IPCC, 2013). The mean climate projections from the CMIP3 and CMIP5 are consistent but the likely ranges of climate change are different due to the different emission scenarios. Special Report on Emission Scenarios (SRES) was used in IPCC AR4 while the Representative Concentration Pathways (RCP) was used in IPCC AR5. Projections from twelve climate models used in CMIP3 have been integrated into the UK climate change projections as explained in the following subsection 2.1.3.

2.1.3. UKCP09 climate change projections

UKCP09 provides probabilistic climate projections using MME approach to make modelling uncertainties explicit, which is an innovative way of presenting climate change projections (Murphy *et al.*, 2010). Modelling uncertainties arise from uncertain parameters used in physical process modelling and imperfect scientific understanding of climate system. The former uncertainty is known as the parameter error and the latter uncertainty is known as the structural error. The parameters which have a great influence on the physical process have been identified based on the latest scientific knowledge. Perturbed Physics Ensemble (PPE) consists of a great number of variants of the HadSM3, i.e. a UK Met Office Hadley Centre global climate models (UKCP09, 2012). The possible outcomes from PPE climate simulations are weighted based on the observation of past climate. Probability Distribution Function (PDF) formed by PPE climate change projections can explain the uncertainties from the parameter error but the structural error.

Climate models from different institutions were developed in different ways due to yet unknown operation of climate systems so that the structural error cannot be covered by PPE which consists variants of a single climate model, i.e. HadSM3. Unlike PPE, twelve different global climate models used in the CMIP3 consist MME which provides alternative and independent climate change projections. Modified PDF by integrating the projections from MME, therefore, can take structural errors into account. The global climate projections, however, are available at 300 km grid resolution which is unsuitable for assessing the impacts of climate change on, for instance, built environment. Thanks to the HadRM3, i.e. a UK Hadley regional climate model which downscaled the GCMs projections, UKCP09 can provide probabilistic climate projections at a horizontal grid resolution of 25km (Murphy *et al.*, 2010). Monthly, seasonal and annual climate projections are available in the UK under three emission scenarios for seven decadal time periods as presented in Table 2-1.

Table 2-1. UKCP09 climate projections. This table was recreated from figure A4.1 in theUKCP09 scientific reports (Murphy et al., 2010)

Variable	Emission scenario	Time period	Temporal average
▪ Mean daily temperature ▪ Mean daily minimum and maximum temperature ▪ Precipitation rate ▪ Humidity ▪ Total cloud ▪ Net surface short and long wave flux ▪ Total downward shortwave flux ▪ Mean sea level pressure (some variables can be provided as both climate change and future climate)	▪ Low (SRES B1) ▪ Medium (SRES A1B) ▪ High (SRES A1FI)	▪ 2020s (2010 - 2039) ▪ 2030s (2020 - 2049) ▪ 2040s (2030 - 2059) ▪ 2050s (2040 - 2069) ▪ 2060s (2050 - 2079) ▪ 2070s (2060 - 2089) ▪ 2080s (2070 - 2099)	▪ Monthly ▪ Seasonal ▪ Annual (Not all variables are available at monthly resolution)

UKCP09 climate projections use SRES (IPCC, 2000), i.e. previous emission scenario which was also used in IPCC AR4 (IPCC, 2007a). As shown in Table 2-1, UKCP09 climate projections can be produced under low, medium and high emission scenarios which correspond to SRES B1, SRES A1B and SRES A1FI respectively. Figure 2-3 presents the climate change in the UK showing low to high percentile increases in mean maximum temperature in summer under high emission scenario, i.e. SRES A1FI for the 2050s and 2080s across the UK. These can be generated by using UK Climate Projections User Interface (UKCP09 UI, 2009). The change in mean maximum summer temperature is very unlikely to be lower than the 10th percentile projection 1.8°C (3.1°C for the 2080s) and higher than the 90th percentile projection 7.5°C (8.1°C for the 2080s) for the 2050s. The 50th percentile UKCP09 projections are 4.3°C and 6.9°C for the 2050s and 2080s respectively. The probabilistic UKCP09 climate projections have been incorporated into a weather generator which can provide future daily and hourly weather data set by the end of the 21st century under three emission scenarios across the UK (Jones *et al.*, 2010). The detailed descriptions of UKCP09 Weather Generator (UKCP09 WG) are presented in subsection 2.5.4.

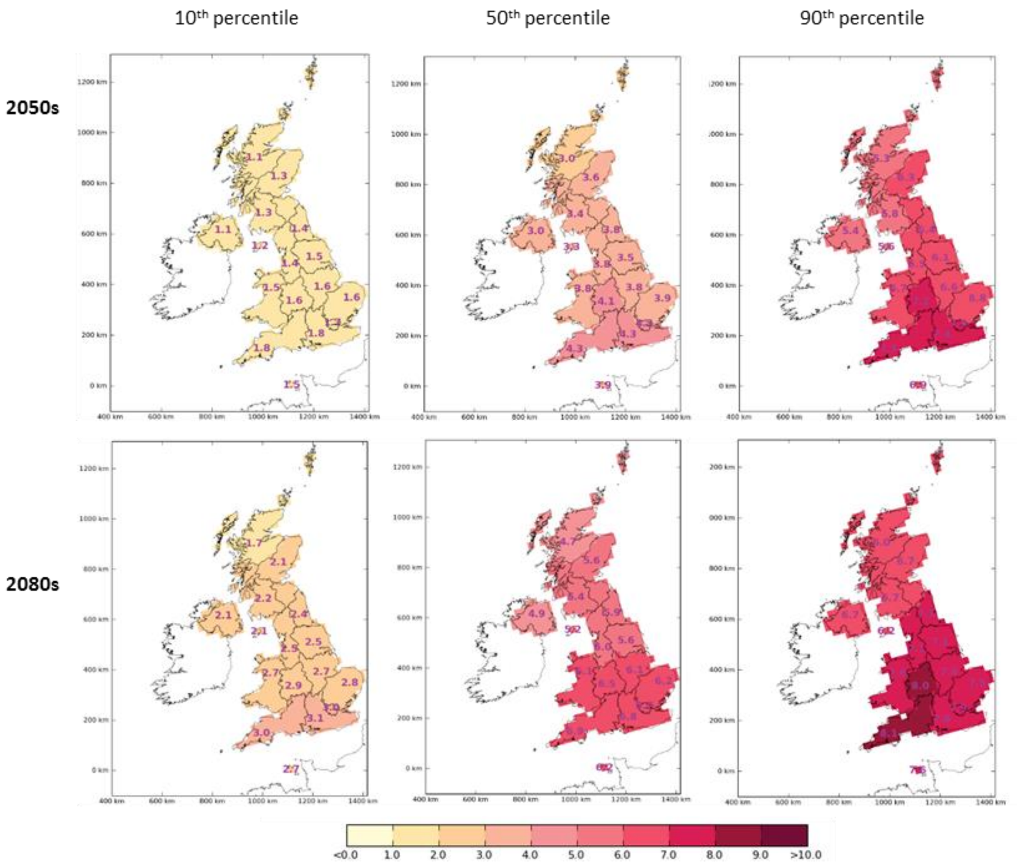


Figure 2-3. The 10th, 50th and 90th probabilistic change in mean maximum temperature (°C) during summer in the 2050s and 2080s across the UK. This climate projections were created using UK Climate Projections User Interface (UKCP09 UI, 2009).

2.1.4. Impacts of global warming on built environment

Human activity has an adverse influence on climate system resulting in more frequent and intensified hot events since the middle of the 20th century (IPCC, 2013). In August 2003 Europe experienced a heat wave which resulted in the terrible heat-related mortality. According to the Earth Policy Institute report (Larsen, 2006a), this European heat wave took approximately 52,000 lives among which 14,729 in France (Fouillet *et al.*, 2006) and 2139 in England and Wales (Johnson *et al.*, 2005). The high nocturnal temperatures lasting from the 1st August to 20th August led to the significant decrease of the heat exchange between buildings and outdoor environment (Glenn R McGregor and Gosling, 2007). As a result, residents who were being exposed to the consecutive days of high indoor temperature were unable to survive the overheating. Vandentorren *et al.* (2006) pointed out that external temperature was the major risk and people living in old buildings (built before 1975) lacking thermal insulation were at a higher risk of deaths than more recent ones; in addition, large window area increased the risk of heat-related deaths while large number of rooms decreased the risk of heat-related deaths; particularly the vulnerable community such as elderly people, who lacked of mobility and were confined to bed or suffering from cardiovascular, neurological, or mental disorders, were more likely at extremely high risk of deaths. It is reported that extremely hot summer in 2003 is likely to become the norm by the 2040s (Stott *et al.*, 2004). The associated annual heat-related deaths will be more than triple by the 2050s and quintuple by the 2080s under a medium emission scenario i.e. SRES A1B compared to the current approximately 2,000 heat-related deaths in the UK (Hajat *et al.*, 2014). Warming climate, growing and ageing population, lack of appropriate building adaptation and awareness of overheating risk to the health are the main reasons for the increasing heat-related mortality estimated (Hajat *et al.*, 2014). Given changing climate scenario, moreover, it was projected that the return period of heat-wave in 2003 is likely to decrease from once per thousands of years to once per hundreds of years (best estimate of 127 years) (Christidis *et al.*, 2015). Thus, it is crucial to investigate into the indoor temperature and associated risk of mortality during hot summer and make sustainable and suitable adaptations for the existing and new buildings, particularly for the naturally ventilated buildings (i.e. non-air conditioned buildings) such as UK dwellings. In order to avoid heat-related deaths, warming climates with different emission scenarios should be taken into account when predicting the risk of overheating in the future.

2.2. Thermal comfort

2.2.1. Definition

Thermal comfort is a state of mind that shows comfortable sensation towards the thermal environment (ASHRAE, 2013; BSI, 2006). When there is a heat balance between the heat production and heat loss to the environment, people express thermal satisfaction. Personal factors (i.e. metabolic rate and clothing) and environmental factors (i.e. air temperature, mean radiant temperature, air velocity and relative humidity) play a key role in determining thermal comfort (CIBSE, 2006a; Fanger, 1970). As thermal comfort is a subjective sensation there is a variation in individual thermal sensation to the same thermal environment. Hence, building practitioners aim to provide indoor thermal environment acceptable by the majority of people rather than a specific person.

2.2.2. Thermal comfort models

Indoor thermal comfort is of importance to the building practitioners when designing or renovating buildings. In order to evaluate the indoor thermal environment and understand the relationship between occupants' thermal perception and environmental parameters, thermal comfort models have been developed in the past decades. Those thermal comfort models can be categorised into static and adaptive models.

a) Static model

One of well-known static thermal comfort models is Fanger's Predicted Mean Vote (PMV) (Fanger, 1970) which predicts the mean vote of a large group of people on seven ASHRAE thermal sensation scales (see Table 2-2) for a given thermal environment. PMV takes account of two personal factors: clothing insulation (clo) and activity level (i.e. metabolic rate (met)), and four environmental factors: air temperature (°C), mean radiant temperature (°C), air velocity (m/s) and relative humidity (%), which affect heat balance of the human body (Fanger, 1970). The heat balance of the human body as well as the experiment data (i.e., a great number of personal comfort votes on seven ASHRAE thermal sensation scales in a climate chamber) are the basis for the PMV model creation (Fanger, 1970).

The heat balance equation for the human body is as follows:

$$M - W = H + E_c + C_{res} + E_{res}\ , \qquad (2\text{-}1)$$

where M is the metabolic rate (W/m^2), W is the effective mechanical power (W/m^2), H is the heat loss from the body surface through convection, radiation and conduction (W/m^2), E_c is the evaporative heat exchange at the skin (W/m^2), C_{res} is the respiratory convective heat exchange (W/m^2), E_{res} is the respiratory evaporative heat exchange (W/m^2).

The PMV model statistically transfers the heat balance to the seven thermal sensation scales as shown in Table 2-2. PMV can be expressed as a function of metabolic rate (M) and thermal load (L) (W/m^2) which is the heat balance between the internal heat production and the heat loss to the environment. PMV is given by

$$PMV = (0.303 \cdot e^{-0.036 \cdot M} + 0.028) \cdot L \qquad (2\text{-}2)$$

and

$$L = M - W - H - E_c - C_{res} - E_{res}\ . \qquad (2\text{-}3)$$

It is true that people express thermal sensation differently for the same thermal environment due to the different individual thermal sensitivity. Fanger (1970) created Predicted Percentage of Dissatisfied (PPD) to indicate the percentage of occupants expressing dissatisfaction towards a given thermal condition. As shown in Figure 2-4 there are still 5% of people expressing discomfort when PMV equals zero due to the different individual thermal preferences. PPD (%) can be calculated as follows:

$$PPD = 100 - 95 \cdot e^{-(0.03353 \cdot PMV^4 + 0.2179 \cdot PMV^2)}\ . \qquad (2\text{-}4)$$

The comfort range of PMV between -0.5 and +0.5 (i.e. PPD <10% as shown in Figure 2-4) is recommended for the indoor thermal comfort (ASHRAE, 2013). The PMV model can estimate indoor thermal comfort of air conditioned buildings very well but non-air-conditioned buildings (Brager and de Dear, 1998; Fanger and Toftum, 2002) as the experimental data used to develop the PMV model was collected from the controlled climate chamber rather than free running or naturally ventilated buildings. The PMV model, however, can be used in non-air conditioned buildings by applying an expectancy factor presented later by Fanger and Toftum (2002). The PMV model considered that the energy is exchanged between clothing surface and external environment. The skin temperature and sweat rate, however, were calculated based merely on activity level with no concern on the influence of solar radiation and wind speed. If the skin is exposed to the direct solar radiation or high wind speed, for instance, the skin temperature as well as the sweat rate will be different from the ones calculated in the PMV model. The PMV is only applicable when people are exposed to a steady-state indoor environment for a long period with a constant metabolic rate as the PMV model was created based on the steady-state heat balance of the human body (Nikolopoulou *et al.*, 2001; Thorsson *et al.*, 2004; Spagnolo and de Dear, 2003; Höppe, 2002; Fanger and Toftum, 2002). The PMV model considers physical aspects (i.e. two personal factors and four environmental parameters) but ignores psychological aspects such as thermal expectation and experience, and duration of exposure to the outdoor environment which also have a great influence on the subjective thermal perception (Thorsson *et al.*, 2004; Höppe, 2002).

Table 2-2. ASHRAE Thermal Sensation Scale (ASHRAE, 2013)

Value	Sensation
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
-1	Slightly cool
-2	Cool
-3	Cold

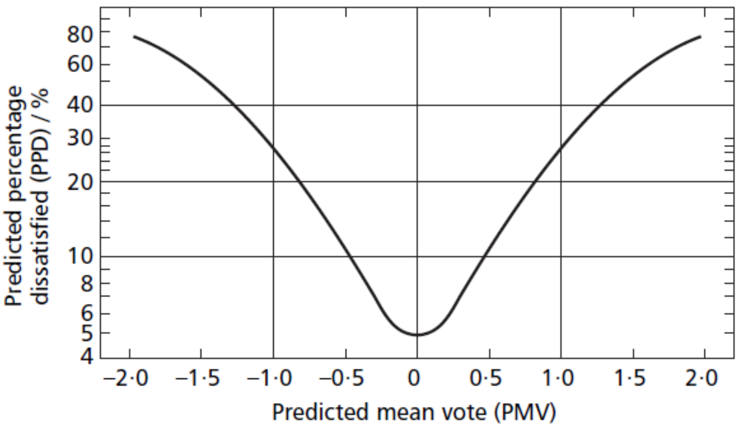


Figure 2-4. PPD as a function of PMV (ASHRAE, 2013)

The Physiologically Equivalent Temperature (PET), which is suitable for both indoor and outdoor thermal comfort assessment, was created based on Munich Energy balance Model for Individuals (MEMI) (Mayer and Höppe, 1987). PET considers two personal factors and four environmental factors like Fanger's PMV. Firstly, human body temperatures (i.e. mean skin and core temperatures) are calculated based on MEMI for a given environment. The air temperature which can keep the body temperatures for a typical standardised indoor environment is then considered as PET (°C) (Höppe, 1993; Mayer and Höppe, 1987). In the typical standardised indoor environment, air temperature is assumed to be equal to radiant temperature, air velocity and water vapour pressure are set to 0.1 m/s and 12 hPa respectively. PET is a thermal index which has been used in German building guideline (VDI, 1998). As shown in Table 2-3 which was originally created by Matzarakis *et al*. (1999), PET is in line with different grades of PMV, thermal perception and physiological stress (Matzarakis and Mayer, 1996). The skin temperature and sweat rate used in PET calculation depends on not only activity level but also ambient climate condition so that it can overcome the shortcoming of the PMV model where the mean skin temperature and sweat rate are calculated based merely on the activity level. Unlike PMV, furthermore, PET is suitable for use in any climate condition. As PET is based on the steady-state heat balance of the human body, it is not appropriate for a short-time exposure i.e. less than one hour (Höppe, 2002). Likewise, other thermal indices based on the steady-state heat balance of the human body, such as PMV, Perceived Temperature (Jendritzky *et al.*, 2000) and outdoor Standard Effective Temperature (Pickup and de Dear, 2000), are not suitable for a short-term thermal comfort assessment. More importantly, static thermal models are likely to overestimate thermal discomfort as behavioural thermal adaptations were not taken into account.

Table 2-3. Thermal indices and their corresponding thermal perception and physiological stress. This table was originally created by Matzarakis et al. (1999).

PET (°C)	PMV	Thermal perception	Physiological stress
	-4.0	Very cold	Extreme cold stress
4	**-3.5**		
	-3.0	Cold	Strong cold stress
8	**-2.5**		
	-2.0	Cool	Moderate cold stress
13	**-1.5**		
	-1.0	Slightly cool	Slight cold stress
18	**-0.5**		
	0	Comfortable	No thermal stress
23	**+0.5**		
	+1.0	Slightly warm	Slight heat stress
29	**+1.5**		
	+2.0	Warm	Moderate heat stress
35	**+2.5**		
	+3.0	Hot	Strong heat stress
41	**+3.5**		
	+4.0	Very hot	Extreme heat stress

b) Adaptive model

Occupants are found to be more likely to adapt to a changing thermal environment in naturally ventilated buildings so that they are tolerant of a wider range of temperatures than those in the air-conditioned buildings (de Dear *et al.*, 1998). The static comfort model such as Fanger's PMV model (Fanger, 1970) does not take account of the behavioural adaptations (e.g., opening/closing windows or blinds, drinking hot/cold water, etc.), physical adaptations (e.g., changes in the physiological responses due to a long exposure to the thermal environmental stress) and psychological adaptations (e.g., changes in thermal expectations) (de Dear *et al.*, 1998). Furthermore, the static comfort models were developed based on the heat balance model which excludes the above three types of adaptations that can have a great influence on the thermal comfort assessment. Alternatively, adaptive comfort model was developed for the naturally ventilated buildings or free running buildings (i.e., non-air-conditioned buildings) which provide more adaptive opportunities for occupants than air-conditioned buildings (Nicol and Humphreys, 2002). Adaptive comfort model uses a changing comfort temperature which depends on the outdoor temperature. As presented in Figure 2-5, the ASNI/ASHRAE adaptive comfort model (ASHRAE, 2013) suggests two comfortable ranges of indoor operative temperatures, which vary with mean monthly outdoor temperatures, accepted by 80% and 90% of the occupants respectively. The ASNI/ASHRAE adaptive comfort temperatures can be calculated by the equation as follows:

$$T_{comf} = 0.31 \cdot T_{om} + 17.8 \tag{2-5}$$

where T_{comf} is adaptive comfort temperature (°C), T_{om} is the monthly mean outdoor temperature (°C).

In addition, the BS EN 15251 adaptive comfort model (BSI, 2007) recommends three acceptable ranges of comfort temperatures for three categories which are described in Table 2-4. It was found that both outdoor temperature and time influenced the comfort temperature in the free running buildings; that is, the more recent daily mean outdoor temperature will have a greater impact on today's comfort temperature (Nicol and Humphreys, 2002). The BS EN 15251 adaptive comfort temperature can be calculated by the equation as follows:

$$T_{comf} = 0.33 \cdot T_{rm} + 18.8 \tag{2-6}$$

and

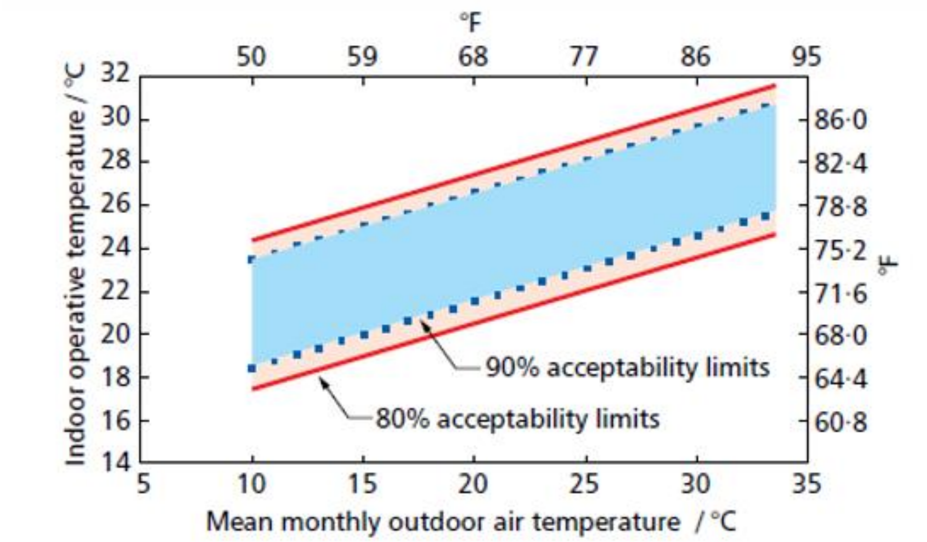
$$T_{rm} = (1 - \alpha) \cdot T_{od-1} + \alpha \cdot T_{rm-1}\ , \tag{2-7}$$

where T_{comf} is adaptive comfort temperature (°C), T_{rm} is running mean daily outdoor temperature (°C), T_{od-1} is previous day mean outdoor temperature (°C), T_{rm-1} is the running mean daily temperature (°C) for the previous day and α is a constant value for which 0.8 is recommended (CIBSE, 2013a). The first day of running mean outdoor temperature can be calculated using daily outdoor temperature for the past seven days as follows:

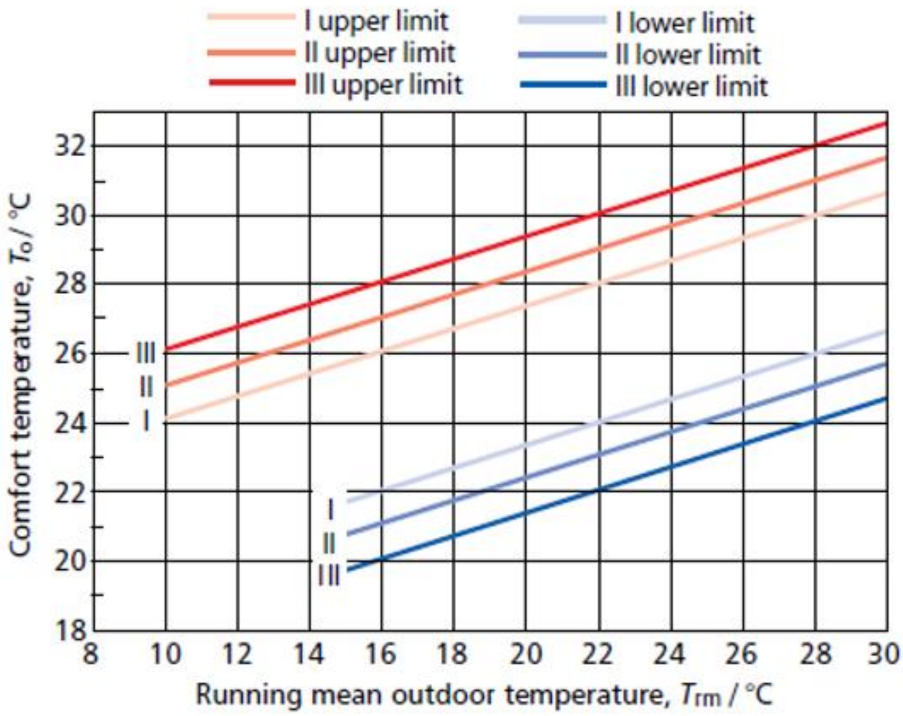
$$\begin{aligned} T_{rm} = (T_{od-1} + 0.8 \cdot T_{od-2} + 0.6 \cdot T_{od-3} + 0.5 \cdot T_{od-4} + 0.4 \cdot T_{od-5} + 0.3 \\ \cdot T_{od-6} + 0.2 \cdot T_{od-7})/3.8 \end{aligned} \tag{2-8}$$

where T_{od-1}, T_{od-2}, etc. are the daily mean outdoor temperatures (°C) for yesterday, the day before and so forth (CIBSE, 2013a).

The CIBSE recommends building practitioners to make indoor thermal environment within the category II limits (CIBSE, 2013a), which corresponding to the PPD less than 10% and PMV no greater than +0.5 and no less than -0.5. Table 2-5 shows the Fanger's PPD and PMV values for the different categories presented in BS EN15251 (BSI, 2007) and ANSI/ASHRAE 55-2013 (ASHRAE, 2013). Unlike the static comfort models, adaptive comfort models do not consider the personal factors (i.e. clothing insulation and metabolic rate) and environmental factors (i.e. mean radiant temperature, air velocity and relative humidity) which are used in the heat balance model for a human body. The adaptive comfort model is appropriate for the existing non-air-conditioned buildings built in the 1990s and located in warm climate zone, whereas it may be inappropriate for the future buildings due to the change in clothing and activity level which might have a great influence on the comfortable bands presented in the adaptive comfort models (Fanger and Toftum, 2002). In addition, Porritt *et al.* (2012) argued that the BS EN15251 adaptive comfort model lacks tests for the T_{rm} above 25°C, which makes it unreliable for use in assessing thermal comfort during extremely hot weather.



(a)



(b)

Figure 2-5. Adaptive comfort models. Graph (a) shows ANSI/ASHRAE 55-2013 adaptive comfort model (ASHRAE, 2013) and graph (b) shows BS EN 15251 (BSI, 2007) adaptive comfort model. This figure is copied from CIBSE TM52 (CIBSE, 2013a)

Table 2-4. Acceptable range of comfort temperatures for free-running buildings with four different categories (from BS EN 15251 (BSI, 2007)).

Category	**Explanation**	**Suggested acceptable range (K)**
I	High level of expectation only used for spaces occupied by very sensitive and fragile persons	± 2
II	Normal expectation (for new buildings and renovations)	± 3
III	A moderate expectation (used for existing buildings)	± 4
IV	Values outside the criteria for the above categories (only acceptable for limited periods)	>4

Table 2-5. Categories of two adaptive comfort models with their corresponding Fanger's PPD and PMV values.

BS EN15251			**ANSI/ASHRAE 55-2013**		
Category	PPD (%)	PMV	Acceptability	PPD (%)	PMV
I	≤ 6	$-0.2 \leq PMV \geq +0.2$	90%	≤ 10	$-0.5 \leq PMV \geq +0.5$
II	≤ 10	$-0.5 \leq PMV \geq +0.5$	80%	≤ 20	$-0.85 \leq PMV \geq +0.85$
III	≤ 15	$-0.7 \leq PMV \geq +0.7$	-	-	-
IV	> 15	PMV < -0.7 PMV > +0.7	-	-	-

2.2.3. Assessment criteria

Various thermal indices have been proposed to judge whether or not a given thermal environment is comfortable. The Effective Temperature (Houghton, 1923), Corrected Effective Temperature (Vernon and Warner, 1932), Wet Bulb Globe Temperature (Yaglou and Minaed, 1957), Operative Temperature (Winslow *et al.*, 1937), and so forth were created based on the relative importance of weather variables on human thermal perception but with no concern for personal factors i.e. clothing insulation and activity level. After then, more complex thermal indices such as PMV/PPD (Fanger, 1970), Standard Effective Temperature (SET) (Gagge *et al.*, 1986) and PET (Hoppe, 1999) have been developed based on the heat balance of the human body which takes account of personal factors in addition to the thermally related weather variables. Interestingly, Humphreys *et al.* (2007) found that the simple thermal indices such as the air temperature and the operative temperature showed a better correlation with the actual thermal sensation votes of occupants compared to the more complex indices such as PMV and SET. However, the simple indices provide too little information about the thermal environment. Alternatively, current research basically used static criteria (e.g. the internal temperature should be lower than the fixed threshold summer temperatures or PMV) and adaptive criteria (e.g. the internal temperature should not exceed the upper limit of adaptive comfort temperature which changes with the external environment) to assess indoor thermal comfort.

a) Static criteria

A constant threshold is used to measure the thermal environment of the buildings. For example, the range of PMV between -0.5 and +0.5 is recommended for mechanically ventilated buildings by BS EN15251 (BSI, 2007). Hence, the indoor PMV +0.5 can be considered as the upper limit for identifying overheating in the buildings. Similarly, indoor PET above 23°C, which is equivalent to PMV +0.5 as shown in Table 2-3, can be considered as the threshold for identifying the thermal discomfort (or thermal stress). CIBSE Guide A (CIBSE, 2006a) recommends two threshold temperatures, i.e. 28°C and 26°C for living rooms and bedrooms respectively. Table 2-6 which was reproduced from Table 1.8 in CIBSE Guide A shows the summertime threshold temperatures for different dwelling types. The internal operative temperatures should not exceed the summertime threshold temperatures for 1% of annual occupied hours. CIBSE Guide A presented that sleep is impaired since the temperature above 24°C which also can be considered as a threshold temperature for the bedroom. According to the Passive House criteria (PHI, 2016), indoor temperatures of the passive house without active cooling should not exceed 25°C for 10%

of hours in a given year. In addition, the Standard Assessment Procedure (SAP) predicts the overheating risk by comparing monthly internal temperature with the different levels of threshold temperatures as presented in Table P3 in SAP 2012 (BRE, 2012) which was reproduced in Table 2-7 below.

Table 2-6. Benchmark summer peak temperatures and overheating criteria recommended by CIBSE Guide A (CIBSE, 2006a)

Building type	**Benchmark summer peak temperature**	**Overheating criterion**
Offices	28°C	1% annual occupied hours over operative temperature of 28°C
Schools	28°C	1% annual occupied hours over operative temperature of 28°C
Dwellings:		
• Living rooms	28°C	1% annual occupied hours over operative temperature of 28°C
• Bedrooms	26°C	1% annual occupied hours over operative temperature of 26°C

Table 2-7. Levels of threshold temperature corresponding to the likelihood of high internal temperature during hot weather used in SAP overheating risk assessment (BRE, 2012).

$\mathbf{T_{threshold}}$	**Likelihood of high internal temperature during hot weather**
< 20.5°C	Not significant
≥ 20.5°C and < 22°C	Slight
≥ 22.0°C and < 23.5°C	Medium
≥ 23.5°C	High

The static criteria are easy to use and preferred when quickly comparing different building designs in terms of the occurrence of high indoor temperatures. The main shortcoming of these static criteria is that they ignore the occupants' behavioural adaptions to warm indoor environment so that the overheating risk is likely to be overestimated (Fanger and Toftum, 2002). Furthermore, the static criteria cannot measure the severity of overheating or thermal discomfort (Mulville and Stravoravdis, 2016). For example, there was a significant difference between the two cases: living room (a) showed operative temperature exceeding 29°C for ten hours and living room (b) exceeds

35°C for ten hours. According to CIBSE Guide A (CIBSE, 2006a) static criterion, however, both cases give the same overheating hours, i.e. ten hours as the criterion considers the occupied hours above the 28°C but ignores the degree exceedance. In fact, people in the living room (b) would be at higher risk of overheating or thermal stress than people in the living room (a). This issue can be addressed by using degree hours which can distinguish the two cases. For instance, degree hours for the living room (a) and (b) are ten and sixty respectively. The degree hour is the cumulative number of the differences between hourly ambient temperatures and the threshold temperatures. There are two types of degree hours: the Heating Degree Hour (HDH) and the Cooling Degree Hour (CDH) which have been primarily used in estimating heating energy demand during winter and cooling energy demand during summer respectively. The CDH has been used as an indicator of the severity of overheating in the previous studies (Porritt *et al.,* 2012; Porritt *et al.*, 2010). The degree hours with weighting factors that depend on the degree exceedance are recommended by BS EN 15251. A greater emphasis can be put on a higher indoor operative temperature. Degree hours can be calculated based on, instead of a static threshold, adaptive comfort temperatures, i.e. changing thresholds to take account of occupants' abilities (e.g., opening window to enable natural ventilation or shutting down the blind to reduce solar gain) to adapt to the external environment.

b) Adaptive criteria

The adaptive criteria are basically associated with the adaptive comfort model. Unlike static criteria which use fixed thresholds, adaptive criteria use changing thresholds (e.g. the upper limit of T_{comf} changes linearly with T_{rm} (see Figure 2-5)). K.J.Lomas and T.Kane (2013) stated that people would tend to adapt to changing temperatures better when staying in free-running buildings compared to staying in air-conditioned buildings. Since the adaptive criteria such as the BS EN 15251 adaptive criteria which are associated with the BS EN 15251 adaptive comfort model (BSI, 2007) that takes occupants' behavioural adaptation into account, they are more appropriate than the static criteria when assessing overheating risk in the free running buildings such as UK dwellings (Lomas and Kane, 2013). Unlike the static criteria such as the one recommended by CIBSE Guide A which is basically used for measuring the occurrence of high indoor temperatures, adaptive criteria (e.g. the BS EN 15251 adaptive criteria) are able to assess both uncomfortably high and low temperatures. In addition, four different categories of the BS EN 15251 adaptive criteria could account for the people with different thermal preferences while the static criteria cannot. However, Beizaee *et al.* (2013) and K.J.Lomas and T.Kane (2013) questioned the validity of the BS EN 15251 adaptive criteria when assessing the thermal comfort in the free-running domestic buildings. The issue is that the BS EN 15251 adaptive comfort model was developed based on the data collected from non-domestic buildings which are apparently different from the domestic buildings in many aspects, for instance, thermal comfort expectations and availability of human behaviour adaptations. The vulnerable group is less likely or even unlikely to take actions to adapt to the external weather. Hence, the adaptive criteria might be not suitable for such group. It is true that the fixed threshold temperatures are closely related to health. According to the Housing Health and Safety Rating System (ODPM, 2006) developed by UK Government, for instance, mortality and stroke increase when the temperature rises above 25°C. Therefore, static criteria might be appropriate for assessing the risk of heat-related morbidity or mortality to vulnerable group (Mavrogianni *et al.*, 2015). Beizaee *et al.* (2013) also have pointed out that people living in the cooler region are able to adapt to lower temperature, vice versa; hence, the adaptive criteria might not be reliable unless they are modified based on the temperature tolerance of people in the regions.

In addition, the adaptive and weighting approaches combined can be used to measure the severity of overheating risk thereby overcoming the shortcoming in the static criteria (Nicol *et al.*, 2009). CIBSE TM49 (CIBSE, 2014) presented Weighted Cooling Degree Hours (WCDH) which can be calculated as follows:

$$WCDH = \sum_{all\ hours} \left(T_{op} - T_{comf}\right)^2 \qquad (2\text{-}9)$$

with

$$T_{op} - T_{comf} > 0, \qquad (2\text{-}10)$$

where T_{op} is operative temperature (°C). Due to the quadratic difference between T_{op} and T_{comf} which places a greater emphasis on more serious discomfort temperature, WCDH is suitable for measuring the severity of overheating.

CIBSE TM52 (CIBSE, 2013a) also recommends three criteria: (1) hours of exceedance (H_e) for measuring the duration of overheating, (2) daily weighted exceedance (W_e) for measuring the severity of overheating, and (3) upper limit temperature (T_{upp}) for examining an absolute maximum temperature for free running buildings. All of the three criteria were based on the difference (*ΔT*) between the T_{op} and the upper limit of comfort temperature presented by the BS EN15251 adaptive comfort model (BSI, 2007). At least two of the three criteria should be satisfied otherwise the indoor environment is regarded as overheating (CIBSE, 2013a).

2.3. Thermal simulation

Indoor thermal comfort can be evaluated via either monitoring (or questionnaire) or computer simulation. Monitoring or questionnaire approach may lead to more realistic results but it is more expensive and time consuming compared to the computer simulation. With the rise of knowledge towards building physics combined with the advent of computers, various building simulation packages have been developed for evaluating energy and thermal performance of buildings. Building simulation package is normally comprised of a user interface and thermodynamic functions, i.e. the simulation engine. Inevitably, there are performance gaps between the absolute building simulation and the real situation due to the uncertainties resulted by, for instance, lack of building description, unpredictable occupants' behaviours, limitations in the thermal simulation packages, and so forth. Thus, it is common to make an assumption on the unknown simulation parameters such as infiltration, internal loads and occupancy profiles according to the empirical knowledge or guidelines. The merit of thermal simulation is that various design alternatives can be quickly tested for comparison, which enables building practitioners to find out the optimal design alternative for the building.

This chapter describes generic building simulation packages and two different simulation methods: static and dynamic thermal simulations which are described in subsection 2.3.1 and subsection 2.3.2 respectively. The reasons behind the selection of dynamic thermal simulation for this study are mentioned in 2.3.3.

2.3.1. Static thermal simulation

Steady-state thermal model is used to predict monthly (or annual) building energy consumption and indoor thermal comfort for a whole building. In addition, the steady-state model can be used to validate the dynamic model. The building simulation packages for use in static thermal simulations are described in this subsection. Though some of them primarily were developed for assessing building energy performance, their outputs such as internal temperature or cooling load can indicate indoor thermal discomfort.

a) BRE Domestic Energy Model (BREDEM)

Building Research Establishment (BRE) has developed BREDEM for calculating the monthly energy consumption of dwellings. Though BREDEM does not take account of thermal comfort analysis, the monthly mean internal temperature and cooling energy consumption from the outputs of BREDEM can be used to evaluate indoor thermal environment.

b) Standard Assessment Procedure (SAP)

In addition, BRE has developed SAP based on the BREDEM calculation methodology. SAP is used for assessing energy performance of dwelling. The outputs include energy use per unit floor area, the CO_2 emissions and the SAP rating (i.e. energy efficiency rating). The SAP rating is displayed in the Energy Performance Certificate (EPC) which must be shown to the owners of the property since April 2008. EPC can be used to compare the energy performance between dwellings and inform improvements in building energy efficiency. Reduced Data SAP (RdSAP) can be used to assess existing dwellings when there is lack of complete input data required for SAP calculation. The Appendix P in the current version of SAP 2012 shows a procedure of overheating risk assessment which however is not considered in the SAP rating. The SAP method calculates mean internal temperature during summer (from June to August) based on dwelling description and monthly weather data (presented in Appendix U: Climate data in SAP 2012 document (BRE, 2012)). The risk of overheating then can be estimated through comparing the mean internal temperature with the overheating threshold temperatures presented in Table 2-7. The limitation of the SAP method is that it uses monthly weather data so that the variation in temperatures, for instance, the daily maximum and minimum temperature are not taken into account when predicting the risk of overheating. Moreover, the climate data presented in SAP 2012 document is only available for 21 regions in the UK so that the SAP method cannot take localised weather into account. Nonetheless, it is useful to investigate overheating risk at a big scale with SAP method that requires much fewer inputs compared to the dynamic building simulation.

c) Cambridge Housing Model (CHM)

Cambridge Architectural Research Limited has developed CHM to estimate domestic energy consumption for England, UK. The housing data from English Housing Survey in 2011 and monthly climate data for twelve regions are used as the inputs for CHM. CHM can perform building energy simulation either for a single house or for the entire English housing stock. The annual building energy consumption, in fact, is calculated based on the methods presented in the SAP 2009 (the latest version is SAP 2012) and RdSAP. CHM also outputs CO2 emission, CHM ratings (i.e. energy efficiency rating), etc. CHM calculates yearly mean internal temperature which can be used to compare the overall indoor thermal comfort between dwelling types or between twelve regions over England.

d) Passive House Planning Package (PHPP) and designPH

Passive House Planning Package (PHPP), i.e. a design tool based on Excel spreadsheets, has been developed by the Passive House Institute (PHI) in Germany. Monthly climate data is used in PHPP. Building practitioners uses PHPP to design passive houses, i.e. high energy efficient and comfortable houses which comply with the passive house standard (PHI, 2016). According to the passive house standard, space cooling or heating demand should be less than 15 kWh/m^2 per year, primary energy demand should be less than 120kWh per year for all domestic usages per square meter of living area, and air change per hour should be less than 0.6, and frequency of overheating (i.e. indoor temperatures > 25°C) less than 10% of a given year. PHI also developed 3D Passive House design Tool termed as designPH (PHI, 2017), which is a plugin for 3D modelling software SketchUp used in architecture design. With its user-friendly 3D modelling interface, the complex geometry information can be imported into PHPP more easily and quickly; the heat loss from the building envelop can be visualised; and building models can be quickly tested with changes in, for instance, locations, orientations, shadings, building specifications, etc.

In summary, both BREDEM and SAP can estimate overheating risk based on the monthly or seasonal mean internal temperature. However, neither of them can measure the severity of overheating risk in that thermal analysis with higher temporal weather time series (e.g. daily or hourly temperatures) is required. Likewise, CHM only carries out yearly simulation primarily for estimating domestic energy consumption and provides the annual mean internal temperatures which cannot uncover the duration and frequency of overheating. PHPP calculates the average overheating for the whole building. Hence, PHPP is not appropriate for use if there are significant differences in overheating between the rooms. For example, overheating risk in the living room and bedrooms can be highly different if there are significant differences in orientation, window to wall ratio, occupancy, etc. In addition, designPH uses PHPP monthly balance based calculation so that it is not an ideal tool for detail overheating risk assessment which needs daily or hourly thermal calculation for different zones in a building.

To sum up, these static building simulation packages can be used to simulate overall monthly or annual indoor thermal comfort but they cannot be used to measure the intensity of overheating for dynamic condition. In order to overcome the limitation of the static thermal simulation, dynamic thermal simulation should be carried out for further investigation into the duration and severity of overheating. This is the main reason for the choice of dynamic thermal simulation packages in this study.

2.3.2. Dynamic thermal simulation

The dynamic building simulation packages have been used to predict building energy performance and indoor thermal comfort in the past decades due to its advantages over static building simulation packages. In contrast to the static thermal simulation which uses simple steady-state thermal model with monthly (or yearly) weather data, dynamic thermal simulation in general uses more complex thermal model with a much higher temporal weather time series e.g. hourly or sub-hourly weather data. The dynamic thermal models take account more comprehensive aspects of building physics including transient thermal balance and non-steady state building operation compared to the static thermal models. The complex thermal model however is not a perfect model because the complex thermal processes in a building have not yet been fully understood. With regard to thermal modelling more complex models do not guarantee more realistic or accurate results as uncertainties arise from more complex simulation parameters which do not exactly match with real life.

Both static and dynamic building simulations assume that the internal temperature distribution is spatially uniform. Dynamic building simulation packages can divide a whole building into several different zones and take account of inter-zone heat-exchange. Thus, dynamic thermal simulation takes longer than static thermal simulation due to the complex thermal model and high temporal weather data. With the rapidly increasing computing power, however, researchers would rarely bother with computation time.

A large number of building simulation packages have been developed over the past decades and most of them are listed in the Building Software Tools Directory (U.S. DOE 2007). Those building simulation packages can be used to predict building energy consumption, thermal, visual and acoustic performance, cost, and so forth. This subsection describes some of widely acknowledged and academically preferred dynamic building simulation packages and focuses on their capability of detailed overheating risk assessment. Finally, two of them: EnergyPlus and DesignBuilder have been selected for this study. The choice for the combination of these two simulation packages have been explained in section 4.1.

a) EnergyPlus

EnergyPlus is an open source building simulation package which was firstly released by U.S. Department Of Energy (U.S. DOE). Input Data File (IDF) editor and EP-Lunch have been developed along with EnergyPlus simulation engine. IDF editor is used for editing IDF while EP-Lunch for selecting single or multiple input and output files. EnergyPlus, which is in fact a simulation engine, has been updated till the time of writing. Different user interfaces can be developed to EnergyPlus for different type of users such as architects, building practitioners, researchers and non-researchers. It has merged two previous powerful building simulation packages: the Building Loads Analysis and System Thermodynamics (BLAST) (Hittle and Lawrie, 1978) and DOE-2 program (Hirsch, 1981) which has been kept updated with funding from U.S. DOE. New features, for example, modular structure which enables researchers to add new modules into the EnergyPlus with less effort, were integrated into EnergyPlus. Both BLAST and DOE-2 were developed to predict building energy consumption and cost with hourly weather data. However, the zone temperatures predicted from BLAST and DOE-2 are inaccurate, which lead to unreliable prediction for building energy consumption and occupant thermal comfort. Neither BLAST nor DOE-2 takes account of feedback from the building system model into thermal loads, which results in inaccurate zone temperature. In contrast, EnergyPlus can predict accurate zone temperatures using the integrated simulation technique, i.e. integrating heat and mass balance simulation and building system simulation. That is, thermal loads calculated based on the heat balance model are used in the building system model for predicting HVAC response which, in turn, affects thermal loads, i.e. zone temperature. EnergyPlus contains a module which can do thermal simulation of natural ventilation. This module is significantly important for overheating risk assessment in the UK dwellings which are in general naturally ventilated during summer. Besides energy consumption and cost, EnergyPlus outputs internal air, operative and radiant temperatures, Fanger PMV/PPD, BS EN 15251 and ASHRAE 55 adaptive comfort temperature; furthermore, it counts when the operative temperature falls into acceptable thermal comfort range, etc. EnergyPlus Weather file (EPW), which contains hourly dry and wet bulb temperature, solar radiation, relative humidity, etc., is a specified weather format for EnergyPlus. This weather format has been used by other software (e.g., Openstudio, DesignBuilder) that was developed based upon EnergyPlus simulation engine, and other proprietary software (e.g. IES <VE> and ESP-r) described below. The details of EPW are presented in subsection 2.5.1.

b) OpenStudio

OpenStudio was developed by National Renewable Energy Laboratory and U.S. DOE to help building practitioners to design more energy efficient buildings. OpenStudio is an application program interface (API) which offers software development platform to the researchers. Thus, researchers are able to add new functions and create their own user interface for specific use. The building performance simulation engine of OpenStudio is EnergyPlus. That is, OpenStudio can provide as much indoor thermal comfort analysis as EnergyPlus can. The OpenStudio SketchUp Plug-in makes building geometry modelling much easier for the users compared to the EnergyPlus. Besides, OpenStudio uses same weather file format (i.e. EPW) as EnergyPlus does.

c) DesignBuilder

Similar to OpenStudio, DesignBuilder uses EnergyPlus as its simulation engine for dynamic thermal simulation. It was developed for the purpose of creating a complex building thermal model much easier than ever before. It consists of an easy-to-use and powerful 3-D building geometry modelling module, simulation engine, and results viewer. In addition, DesignBuilder integrates other modules capable of, for instance, lighting simulation, 3D computational fluid dynamics (CFD) analysis and so on. DesginBuilder provides templates for many countries over the world according to their respective building regulations. Majority of parameters in the template are set by default, which helps users who have insufficient knowledge about complex building system or lack of building information to carry out building simulation with little concern about the unfamiliar settings in the model. Furthermore, DesignBuilder library contains a large number of building materials and construction components (e.g. single or cavity wall, timber or concrete floor, occupied or unoccupied roof, different insulation levels, single or double glazing window) and recommended occupancy profiles for use in different room types. Full building information required for dynamic building simulation quite often is not available. The DesignBuilder template and library data, therefore, can facilitate the building modelling process. DesignBuilder does not include entire functionalities of EnergyPlus. Fortunately, the thermal models created by DesignBuilder can be exported as the .idf file which, then, can be further processed with EnergyPlus IDF editor. DesignBuilder also uses EPW which are available for over 2,100 locations around the world.

d) Integrated Environmental Solutions <Virtual Environment> (IES <VE>)

Integrated Environmental Solutions <Virtual Environment> (IES <VE>) can be used for the detailed evaluation of building energy consumption and thermal comfort. IES <VE> consists of various modules which enable 3D building geometry modelling, thermal performance analysis, HAVC modelling, lighting simulation, cost analysis, etc. In addition, IES <VE> can do CFD analysis. Regarding the weather file format, EPW files (see subsection 2.5.1) can be used in IES

<VE> software in addition to its own specific weather file format, i.e. fwt (IES, 2014) which contains hourly dry and wet bulb temperature, direct and diffuse solar radiation, solar altitude and azimuth, wind speed and direction, cloud cover, and atmospheric pressure.

e) Environmental Systems Performance, Research version (ESP-r)

The initial prototype of Environmental Systems Performance Research version (ESP-r) was created by Clarke (1977). ESP-r has been updated by Energy Systems Research Unit (ESRU), University of Strathclyde, UK since 1987. It is an open source building simulation package which is designed for the Linux operating system. Similar to the EnergyPlus and the IES <VE>, the ESP-r is an integrated building simulation software which can predict building energy use and environmental performance, i.e. thermal, visual and acoustic performance. Like IES <VE>, ESP-r contains CFD analysis. Due to the free access to the ESP-r source code, international development communities are contributing to the improvement of the ESP-r so that users are able to create a thermal model as realistic as possible to the actual building. This, however, is not a user-friendly software as expertise in building physics is required in learning ESP-r. Furthermore, there are lack of detailed tutorial materials. Therefore, it is recommended to learn it with a mentor. More details can be found in ESRU (2017).

f) Tas Engineering

Tas Engineering (EDSL, 2015) was firstly developed by Environmental Design Solutions Limited (EDSL) in 1989 and has been kept updated so far. Similar to the above dynamic building simulation packages, Tas Engineering serves to appraise the energy and thermal performance of buildings, operating cost, CO2 emission, etc. It consists of user-friendly geometry modelling interface, simulation engine and results viewer, which is similar to the DesignBuilder. As mentioned above DesignBuilder uses EnergyPlus while Tas Engineering uses its own simulation engine. Tas Engineering helps building practitioners to model large and complex buildings with less effort. The weather data used by Tas Engineering consists of five weather variables: temperature, solar radiation, humidity, wind speed and direction. The weather data is available over 2,500 sites over the world.

2.3.3. Summary

Static simulation packages consider a few factors and simple algorithms to estimate the steady state of building energy and thermal performance. Static thermal simulation is simple so that it is less time-consuming than the dynamic thermal simulation. Static simulation packages are, in general, perform monthly thermal simulation. Therefore, it is inappropriate for examining the severity of overheating risk which requires typically hourly thermal simulation. More importantly, static thermal simulation is unable to consider transient heat balance and variation in air temperature caused by natural ventilation, solar gain, internal gain, and so forth. Dynamic simulation packages consider more detailed weather condition, building information and operation strategy. The natural ventilation which has a significant influence on the indoor thermal environment is considered in the dynamic thermal simulation. The complete set of detailed input data, however, is not easy to obtain to create dynamic thermal models. Hence, assumptions have to be made on unknown modelling parameters, which might not match to the real life. Though dynamic thermal simulation is superior to the static thermal simulation, the gaps between the outputs of simulation and the real world are unavoidable. The dynamic simulation engines, in general, calculate the indoor temperature at one point per zone, assuming that the zone temperature is spatially uniform, in order to simplify the thermal calculation within the tolerant range of accuracy. This approach is inappropriate for a large open space such as auditoriums and atriums where the distribution of temperature is non-uniform. CFD should be used for such a large single space where the thermal condition is highly diverse. CFD method is even more computationally expensive than the dynamic thermal simulation. Regarding overheating risk assessment in the living rooms and bedrooms, however, this variation in temperature for such small spaces is negligible. In short, dynamic thermal simulation is preferable when predicting the duration as well as the severity of overheating. Thus, the dynamic simulation packages have been chosen for this study.

2.4. Thermal modelling for UK dwellings

With a powerful dynamic simulation package, detailed measurement of a real building and localised weather data, the accurate overheating risk assessment is achievable. This study aims to assess overheating risk via dynamic thermal simulation for a large number of dwellings across a city. In order to create a large number of thermal models as realistic as possible, measured dwelling information for every single dwelling is necessary. However, it is hard to obtain such dwelling information for use in the creation of dynamic thermal models due to the high cost and time-consuming. Most of the previous research relied on the existing housing survey data set which does not contain enough information to create realistic dynamic thermal models. Subsection 2.4.1 reviews on the available nationwide housing stock data set. In addition, standard thermal models for the UK dwellings from different sources are presented in subsection 2.4.2. Most importantly, shortcomings in the thermal models used by the previous studies due to the lack of detailed dwelling information are pointed out in subsection 2.4.3. With regard to realistic thermal models, the necessity of detailed dwelling measurement including surrounding shading is discussed in subsection 2.4.4.

2.4.1. UK housing survey

a) English Housing Survey (EHS) 2015-2016

The Department for Communities and Local Government (DCLG) publishes annual English Housing Survey (EHS) headline report. The full report is released in two years later. EHS 2015-2016 report (DCLG, 2017) contains the latest English housing stock profile statistic (e.g. the property age, house type and size of dwellings), house condition (e.g. percentage of dwellings failed to meet the Decent Homes Standard and damp problems), energy efficiency (e.g. SAP rating and insulation level) and smoke and carbon monoxide alarms for around 17,000 randomly selected samples out of approximately 22.8 million households in England. The housing survey consists of interview survey, physical survey and market value survey. The physical survey includes information about dwelling type, age, construction, dimensions of flat, occupancy (i.e. occupied or vacant), heating system, state of repair, health and safety assessment, etc. for approximately 8,000 dwellings which could be categorized into detached houses, semi-detached houses, end and mid terraced houses, bungalows and flats. The physical survey, therefore, is useful when creating thermal models of UK domestic buildings.

b) Energy Follow Up Survey (EFUS) 2011

Energy Follow Up Survey (EFUS) (DECC and BRE, 2016) also is a national survey which used sub-samples of EHS. EFUS aimed to investigate the patterns and usage of domestic energy which were used to update national calculation methods such as SAP and BREDEM, and also to inform energy efficiency policy. The interview questionnaire and electricity meters (monitoring every 10 seconds for six to nine months for 79 households) were used to collect dwelling information and measure energy consumption. In addition, EFUS measured the thermal comfort during winter and overheating during summer via interview and internal temperature measurement (monitoring every 20 minutes for one year for 823 households) in three rooms: living room, main bedroom and hallway.

Both EHS and EFUS cannot provide enough dwelling information required for dynamic thermal modelling as these housing survey data were not primarily collected for the purpose of thermal modelling. Furthermore, neither EHS nor EFUS considered the surrounding shading which may have a significant influence on daytime overheating risk.

c) Energy Performance Certificate (EPC) data

Energy Performance Certificate (EPC) shows energy efficiency rating, environmental impact (CO_2) rating, energy use, energy costs, and recommendations on how to improve energy efficiency and save money. An accredited energy assessor produces EPC for a dwelling based on simple energy efficiency assessment procedure RdSAP (mentioned in subsection 2.3.1). EPC is a mandatory requirement when a property is constructed, sold or let in England and Wales. Heating system, heating fuel, dwelling type, construction date, wall and loft insulation, glazing type, total floor area, etc. also are shown in EPC. EPC data is freely accessible. The EPC data alone, however, contains far less building information than what is required for dynamic thermal modelling.

d) Home Energy Efficiency Database (HEED)

Home Energy Efficiency Database (HEED) (EST, 2013) was created and managed by the Energy Saving Trust. The reports generated based on the aggregated data available from HEED is valuable for government to understand and improve energy efficiency of houses. Overall HEED data coverage is 48.9% of houses in the UK. It contains dwelling characteristics (e.g. dwelling type, age, wall and glazing types), heating systems (e.g. heating system, control and main heating fuel), insulation (e.g. wall and loft insulation, hot water tank insulation) and microgeneration (e.g.

heat pumps, solar thermal and photovoltaic systems). Notwithstanding, HEED cannot provide all the building information required for creating dynamic thermal models of English houses.

e) National Energy Efficiency Data-Framework (NEED)

National Energy Efficiency Data-Framework (NEED) (DECC, 2012) provides information about energy consumption and energy efficiency retrofit measures for both domestic and non-domestic buildings in England and Wales. The NEED data was collected from different sources, for example, housing demographics from EPC and Valuation Office Agency (which is a council tax database including property characteristics in the UK), and energy efficiency measures from HEED.

Both HEED and NEED are composed of data provided by various sources (e.g. local authorities and energy suppliers from industries) and schemes (e.g. fuel poverty scheme) which used different measurements and periods. Thus, their data quality as well as the data coverage are different. Hence, those dataset should not be used for direct comparison between houses or regions. Similar to other housing survey data, neither HEED nor NEED provides enough dwelling information for realistic dynamic thermal modelling as the data was primarily collected for informing government energy efficiency plan rather than dynamic thermal modelling.

f) Home Analytics

Energy Saving Trust (EST) also developed Home Analytics (EST, 2017) which was made up of data set from several sources such as HEED and EPC data. Similar to HEED, Home Analytics is used to assist the government in making policy to improve energy efficiency, install renewable microgeneration and solve fuel poverty issue. Compared with the HEED, Home Analytics offers more comprehensive housing stock data including property age, type, roof orientation, wall and glazing type, insulation level, the number of bedrooms, and footprint of dwelling for over 95% of addresses in the UK. Therefore, it is useful to map dwelling energy efficiency in the UK. However, the key elements for thermal comfort assessment, e.g. glazing area, opening area, surrounding shading, etc. are excluded.

In summary, nationwide housing survey data, in general, was collected for the purpose of investigating current building energy efficiency. UK government makes policy to improve building energy efficiency and meet emission reduction target based on the analysis of these housing survey data. Unfortunately, none of the above housing survey data set provides a complete set of information required for dynamic thermal modelling. In particular, key elements such as landscape context, glazing ratio and opening ratio to overheating risk assessment are missing in these survey data. Hence, measurement of these key elements is necessary to create more reliable and realistic thermal models. The approach to measuring a number of dwellings including local shadings at the address level is described in section 4.3.1. Due to the high cost and time-consuming, rather than creating the dynamic thermal model based on individual measurement, previous studies have used standard models or dwelling archetypes presented in the following subsection 2.4.2.

2.4.2. Standard models for UK dwellings

a) Four UK standard dwelling models (Allen and Pinney, 1990)

The Building Environmental Performance Analysis Club (BEPAC) created standard thermal models for UK dwellings. All of the necessary building information for standard UK dwellings can be found in BEPAC Technical Note (Allen and Pinney, 1990); for example, geometry information for four UK dwelling types, i.e. detached, semi-detached, terraced and bungalow, typical construction and thermal properties of dwelling elements, radiator sizes, infiltration rates, typical occupancy schedules and internal gains. This BEPAC Technical Note has been used in current modelling-based research on thermal comfort and energy performance (Liu and Coley, 2015a, b; Gupta and Gregg, 2012; Gupta and Gregg, 2013; Porritt *et al.*, 2012; Lee and Levermore, 2013). However, the BEPAC Technical Note does not consider all UK dwelling types; for example flat, three story dwelling, one or four bedroom dwellings and houses with extension or garage were not included. The BEPAC recommended to consider more examples of construction types such as solid walls and suspended floors in the future work.

b) Fifteen London dwelling archetypes (Mavrogianni *et al.*, 2012)

Mavrogianni *et al.* (2012) selected fifteen dwelling archetypes for the housing stocks in London. The data on built form and construction age for individual houses in London were collected from Geographic Information System (GIS) database. However, most of the data were obtained from the north west of the Greater London Area. Thus, the data collected merely accounted for 29.2% of the London housing stocks. The different built forms were classified into eighteen categories while the different construction ages into eight age bands (Mavrogianni *et al.*, 2012). Then, fifteen of the most common combinations of built form and construction age band have been selected as dwelling archetypes. The fifteen dwelling archetypes included twenty-seven variants such as ground, mid and top floors accounted for 76% of all collected samples, and therefore represented around 22% (=29.2% × 76%) of total housing stocks in London. The building height and footprint area of each dwelling archetype were averaged from GIS database. The average room height and floor area were specified according to the construction date, assumed roof height, wall and floor thickness, and also the values recommended by RdSAP (BRE, 2005); while window area was calculated as a function of built form and age. Mavrogianni *et al.* (2012) also used a typical internal layout for each archetype. The typical constructions, e.g. wall types, floor types and window types, found in the EHS (DCLG, 2011a) and the RdSAP (BRE, 2005) were applied to the dwelling archetypes. There is, however, concern about using the window area in the dynamic thermal simulation as the glazing area, in fact, is a key factor to solar heat gain. There would be significant difference between the window area and the glazing area due to the size of window frame.

2.4.3. Shortcomings in use of standard dwelling models

This subsection discusses the limitations from using the UK standard dwelling models and models of London dwelling archetypes. The UK standard dwelling models can be used to test different adaption measures to find out the most effective one with regard to improving energy and thermal performance of domestic buildings. The London dwelling archetypes generally were augmented with various building characteristics, e.g. building orientations, insulation levels and external shadings. Then, a great number of dynamic thermal models can be generated to cover the likely range of domestic building types. Previous studies which used the UK standard dwelling models and London dwelling archetypes have been reviewed below.

a) Use of UK standard dwelling models (Allen and Pinney, 1990)

Gupta and Gregg (2012) used three UK standard dwelling models, i.e. detached, semi-detached and mid-terraced houses presented in BEPAC Technical Note (Allen and Pinney, 1990) and the purpose built flat (central flat) to predict the impacts of warming climate on thermal comfort and energy consumption of existing dwellings located in Oxford, UK. They suggested the passive adaptation measures to effectively minimise the adverse impacts of warming climate. Different adaptation measures, e.g. installing shading device, changing glazing types, retrofitting wall insulation, ventilation types, etc. have been tested. Different packages of adaptation measures also have been tested. According to the comparison in terms of their effectiveness in reducing overheating hours (i.e. duration when internal temperature was above or equal to 28°C), the most effective passive adaptation option for all of four standard dwelling types was using shutters to minimise solar gains. Gupta and Gregg (2012) also found that the overheating risk of these standard dwellings would never be completely removed even with the most effective option. However, this would raise a question that if the conclusions still remain true for other dwelling types such as ground/top floor flat and bungalow. After this study, Gupta and Gregg (2013) used dwelling archetypes, i.e. mid-terraced, detached, central flat and semi-detached houses with dominant orientation (i.e. southwest or northwest) to predict overheating risk and test passive adaptation options under a warming climate in six neighbourhoods in the UK. A single dwelling archetype with a dominant orientation and unique construction type was selected for representing most of dwellings in each neighbourhood. Thus, the predicted risk of overheating was uniform across the neighbourhood, which might not be able to represent the real situation. The selected dwelling archetypes for two of neighbourhoods in fact accounted for less than 25% of total housing stocks; that is, variation in dwelling types across the neighbourhoods was not fully captured.

b) Use of fifteen London dwelling archetypes (Mavrogianni *et al*., 2012)

Mavrogianni *et al.* (2012) used EnergyPlus to model 3,456 different dwellings which were the unique combinations of the fifteen London dwelling archetypes (including ground floor, mid-floor and top floor flats), 2 different insulation levels (for external walls, floor, roof and window), 4 building orientations and 2 external environment morphologies. The impacts of these variants on living room temperatures have been examined via 3,456 dynamic thermal simulations. Mavrogianni *et al.* (2012) found that the variation within dwelling type was greater than the variation between the 15 dwelling archetypes. In addition, top floor flats were likely to be at a higher risk of overheating than the mid-floor and ground floor flats. Taylor *et al.* (2014) used the same 3,456 dwelling variants with different climate conditions (i.e. using current and future weather files for six UK locations) in order to examine the influence of the climate conditions on the variation in the risk of overheating among the dwellings. In total 41,472 (i.e. 3,456 unique dwellings × (6 current weather files + 6 future weather files)) dynamic thermal simulations have been carried out. One of the key findings was that the variation in living room temperatures (i.e. daytime temperatures) in London was greater than the other five locations; in contrast, the variation in bedroom temperatures among London dwellings was the smallest of all locations. There were great variations in the risk of overheating among the six locations in the UK, which indicated that locations, i.e. regional weather conditions were significantly important when analysing the building thermal performance (Taylor *et al*., 2014).

As mentioned above, the fifteen London dwelling archetypes only represented 22% of London housing stocks. In addition, the important building characteristics such as glazing ratio and opening ratio were not taken into account when examining the indoor summer temperatures. Furthermore, Taylor *et al.* (2014) used the London dwelling archetypes for other locations where the built forms and building fabrics could be very different from the London housing stocks. Therefore, the key findings from Mavrogianni *et al.* (2012) and Taylor *et al.* (2014) should be treated with caution.

Oikonomou *et al.* (2012) have tried to predict variation in indoor temperatures across London taking Urban Heat Island (UHI) and future climate into account. EnergyPlus was used to model domestic dwellings by augmenting the fifteen London dwelling archetypes with variants such as location (with or without shading effect), orientation (facing south, north, east or west) and ventilation mode (with or without night ventilation). It was assumed that the shading comes from the adjacent building with similar height and the shading effect depends on location, i.e. density of the city. The construction data and the thermal properties were derived from EHS data (DCLG, 2011) and SAP data (BRE, 2005) respectively. In total, 10,368 thermal models were generated to cover likely range of dwelling types in London (Oikonomou *et al.*, 2012). In reality, the surrounding shading effect on ground and top floor might be different within the same dwelling; furthermore, there would be a great variation in the height of the adjacent buildings. If using measured external shading rather than making an assumption on the shading effect, the prediction of variation in indoor temperatures in London would be more convincing.

2.4.4. Summary

The detailed building information required for thermal modelling at a large scale, e.g. citywide or nationwide is rarely available. Hence, a few representative thermal models have been used in the previous assessment of overheating risk. The BEPAC Technical Note (Allen and Pinney, 1990) provides basic dwelling information (e.g. geometry, construction, glazing ratio, occupancy and internal gains) for modelling a few UK typical dwelling types. Thermal models of other typical dwelling types, such as flat, are excluded. As stated above, the UK standard models were useful when testing adaptation measures against changing climate for the purpose of reducing CO_2 emissions from the domestic building sector whilst offering safe and comfortable indoor environment to the people. A large number of the different dwelling thermal models representative of, for example, the citywide housing stocks can be produced by modifying the UK standard models based on the likely range of dwelling variants. The dwelling archetypes such as the fifteen London dwelling archetypes (Mavrogianni *et al*., 2012) can be selected based on the regional dwelling typologies and age band. A great number of dwelling thermal models also can be generated by augmenting the dwelling archetypes with different dwelling variants as have done in previous studies stated above. In short, both the UK standard dwelling models and dwelling archetypes are useful when a large number of thermal models are required for investigating the variation in overheating risk across a city or a country. This study focuses on spatial variation in overheating risk considering variability in not only localised weather but also dwelling characteristics and context. If the key elements such as local shading, glazing ratio and opening ratio, which have been assumed or paid little attention in previous studies, could be measured and then considered in the dynamic thermal models, the assessment of overheating risk would be more convincing than ever before.

2.5. Weather years for building simulation

In addition to the building information, weather data is an essential input for dynamic thermal modelling. The most popular weather file format, i.e. EnergyPlus Weather (.epw) is described in subsection 2.5.1. Weather files can be divided into two types of weather year: one is the typical year, e.g. CIBSE Test Reference Year (TRY) which is used for predicting building energy performance, the other is the warmer than typical year, e.g. CIBSE Design Summer Year (DSY) which is used for assessing overheating risk in naturally ventilated buildings. The methods used to create both types of weather years are presented in subsection 2.5.2 and 2.5.3 respectively. In addition, the methods used to obtain future weather data (see subsection 2.5.4) and the existing approaches to the creation future summer years (see subsection 2.5.5) for the assessment of overheating risk under a changing climate are presented below. Different approaches to the creation of future summer years have been critically reviewed as this is the most important part of this study which aimed to develop alternative approaches to overcome the main shortcomings of the existing future summer years.

2.5.1. Weather file format

Building simulation packages have their own specific weather data input format. This subsection describes the '.epw' format which was used in EnergyPlus. As mentioned in subsection 2.3.2, EnergyPlus is the basis for several dynamic simulation packages, such as OpenStudio and DesignBuilder, which have made the '.epw' file format popular. In addition, the '.epw' file can be read by other proprietary dynamic simulation packages such as IES and ESP-r. U.S. DOE has provided '.epw' files over 2,100 locations around the world so far. The '.epw' file is in Comma Separated Values (CSV) format. Therefore, it is convenient to convert it to different weather formats to be used in other simulation packages.

The 'epw' file contains headers and hourly weather variables as shown in Figure 2-6. The eight headers are (1) location, (2) design condition, (3) typical/extreme periods, (4) monthly ground temperatures (°C), (5) holiday/daylighting saving, (6) comments 1, (7) comments 2 and (8) data periods. The hourly weather variables are presented from the ninth line. Each weather variable and its unit are shown in Table 2-8.

Table 2-8. Variables and units for the EPW file format (Big Ladder Software, 2017).

Variables	Unit	Description
Year	-	Not required
Month	-	Required
Day	-	Required
Hour	-	Required
Minute	-	Not required
Uncertainty flags	-	Not used in building simulation
Dry bulb temperature	°C	Valid range from -70°C to 70°C
Dew point temperature	°C	Valid range from -70°C to 70°C
Relative humidity	%	Valid range from 0% to 100%
Atmospheric pressure	Pa	Valid range from 31,000 to 120,000
Extra-terrestrial horizontal radiation	Wh/m^2	Not used in building simulation
Extra-terrestrial direct radiation	Wh/m^2	Not used in building simulation
Horizontal infrared radiation intensity	Wh/m^2	Required in EnergyPlus and ESP-r
Global horizontal radiation	Wh/m^2	Not required
Direct normal radiation	Wh/m^2	Required
Diffuse horizontal radiation	Wh/m^2	Required
Global horizontal illuminance	lux	Not used in building simulation
Direct normal illuminance	lux	Not used in building simulation
Diffuse horizontal illuminance	lux	Not used in building simulation
Zenith luminance	Cd/m^2	Not used in building simulation
Wind direction	degree	Range from 0 to 360
Wind speed	m/s	Valid range from 0 to 40
Total sky cover[a]	deca	Valid range from 0 to 10
Opaque sky cover[a]	deca	Valid range from 0 to 10
Visibility	km	Not used in building simulation
Ceiling height	m	Not used in building simulation
Present weather observation	-	Not used in building simulation
Present weather code	-	Not used in building simulation
Precipitable water	mm	Not used in building simulation
Aerosol optical depth	-	Not used in building simulation
Snow depth[b]	cm	Required when there is snow on the ground
Days since last snow fall	-	Not used in building simulation

[a]Opaque sky cover is not used in simulation but it is used to calculate horizontal infrared radiation intensity when this field is missing.
[b]Snow depth is used to change the ground reflectance.

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LOCATION,5350185,-,UK,WG data,03772 ,51.525,-0.09,0, 25
DESIGN CONDITIONS,0
TYPICAL/EXTREME PERIODS,0
GROUND TEMPERATURES,1,1.0,,,,8.9,8.7,9.1,10.2,11.6,12.9,13.9,14.2,13.7,12.6,11.2,10.2
HOLIDAYS/DAYLIGHT SAVINGS,No,0,0,0
COMMENTS 1,created by using UKCP09 weather generator output the data contained in this file is copyright University of Exeter and is subject to the terms and conditions of use
COMMENTS 2,wind speed wind direction and pressure based on observations at station id 03772
DATA PERIODS,1,1,Data,Sunday,1/1,12/31
1970,1,1,1,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,-2,-5.4,75,99600,0,0,297,0,0,0,0,0,0,0,210,3.6,5,2,9999,99999,9,999999999,0,999,999,99
1970,1,1,2,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,-1.2,-2.7,88,99600,0,0,306,0,0,0,0,0,0,0,210,3.8,5,2,9999,99999,9,999999999,0,999,999,99
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1970,1,1,4,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,0.6,-0.5,92,99600,0,0,318,0,0,0,0,0,0,0,200,4.1,6,3,9999,99999,9,999999999,0,999,999,99
1970,1,1,5,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,0,-0.7,94,99600,0,0,315,0,0,0,0,0,0,0,200,4.3,8,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,6,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,-0.3,-0.4,99,99600,0,0,314,0,0,0,0,0,0,0,190,4.5,8,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,7,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,0.5,-0.4,93,99600,0,0,318,0,0,0,0,0,0,0,190,4.6,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,8,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,-0.6,-1.5,93,99600,0,0,312,0,0,0,0,0,0,0,190,4.8,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,9,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,-0.7,-1.4,94,99600,56,1414,312,12.4,0,12.4,1406,0,1408,425,200,5,10,5,9999,99999,9,999999999,0,999,999,99
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1970,1,1,11,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,3.4,1.1,81,99600,309,1414,332,42.2,0,42.2,4946,0,4956,1693,200,6,10,5,9999,99999,9,999999999,0,999,999,99
1970,1,1,12,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,3.4,0.4,76,99600,366,1414,331,159.8,220.3,102.8,34271,17462,12532,2023,210,6.9,8,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,13,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,5.8,1.4,67,99600,369,1414,343,200.5,451.9,82.6,56709,36088,11289,1514,210,7.7,4,2,9999,99999,9,999999999,0,999,999,99
1970,1,1,14,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,5.9,0.6,61,99600,317,1414,341,168.3,441.2,69.3,52454,34271,10149,1214,200,7.5,4,2,9999,99999,9,999999999,0,999,999,99
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1970,1,1,16,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,5.8,1.4,67,99600,71,1414,344,15.3,0,15.3,1730,0,1733,523,180,7.2,8,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,17,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,5.8,1.3,66,99600,0,0,343,0,0,0,0,0,0,0,160,6,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,18,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,5.1,0.1,63,99600,0,0,339,0,0,0,0,0,0,0,150,4.8,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,19,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,3.2,-1.2,72,99600,0,0,330,0,0,0,0,0,0,0,140,3.6,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,20,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,2.7,0.3,80,99600,0,0,328,0,0,0,0,0,0,0,120,3.8,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,21,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,2.3,0.4,84,99500,0,0,326,0,0,0,0,0,0,0,110,3.9,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,22,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,1.7,-1.5,78,99500,0,0,323,0,0,0,0,0,0,0,100,4.1,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,23,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,0.4,-3.1,75,99500,0,0,316,0,0,0,0,0,0,0,80,3.9,9,4,9999,99999,9,999999999,0,999,999,99
1970,1,1,24,60,*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?*?,1.7,-2.1,74,99500,0,0,323,0,0,0,0,0,0,0,60,3.8,9,4,9999,99999,9,999999999,0,999,999,99
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Figure 2-6. An example of the EPW file for London. Weather data for the first day of the year is shown. This EPW file was created by Eames et al. (2011)

2.5.2. Typical reference year methods

A great effort has been made to exclude the extreme weather condition and produce a year closest to the long-term weather data series. Typical reference year is a single year which is supposed to represent decades of historical observed weather conditions for a location. Typical reference years have been used to predict the building energy consumption and carbon emissions that can represent a long-term average. It is essential to use typical reference years when comparing the energy efficiency of different building designs. There are two types of typical reference year: one is a continuous year and the other is a composite year. The continuous year consists of hourly weather data from a single year. In contrast, the composite year consists of twelve most representative months, each being selected from different years. This subsection describes and discusses previous methods used to create two types of typical reference years.

a) Continuous year

The first attempt to construct typical reference year in the UK was made by Holmes and Hitchin (1978) who produced the CIBSE Example Weather Year (EWY) to represent long-term weather condition. They selected an entire year out of a set of multi-year hourly weather data based on the six parameters, i.e. total irradiation on horizontal surface, diffuse radiation on the horizontal, daily mean wind speed, daily mean, maximum and minimum dry bulb temperature and infiltration number which is a function of wind speed and dry bulb temperature. Holmes and Hitchin (1978) used a simple method to select an entire year from around 20 years of observed weather data. Firstly, the year with one or more monthly mean values away from more than 2 standard deviations of the overall monthly mean value (i.e. the monthly mean values averaged over all candidate years) was discarded. From the rest of the candidate years, then, the year with the highest deviation from the overall monthly mean value was discarded. Finally, the last survival year becomes the EWY. The EWY is a continuous year (starting from October to September, i.e. 1st October in 1970 to 30th September in 1971) so that there are no discontinuities in the weather sequence. Nevertheless, it is difficult to find 20 years' worth of complete data as candidate years for the EWY selection. The simple method presented by Holmes and Hitchin (1978) cannot guarantee the selected EWY representative of long-term weather conditions for the area with a limited number of candidate years.

b) Composite year

Different from the EWY, the TRY is a composite year which has been available for fourteen UK locations since 2006 (CIBSE, 2013b). The TRYs contain hourly weather data which have been used to predict the energy performance of buildings. Levermore and Parkinson (2006) created the TRY using around 21 years of observed data (from 1983 to 2004) based on Finkelstein-Schafer (FS) statistic method (Finkelstein and Schafer, 1971) for fourteen UK sites. Eames *et al.* (2015) have recently updated the TRYs using typically 30 years of weather data (from 1984 to 2013). The TRY consists of twelve representative months. January in a TRY, for example, was selected from 30 Januaries of overall years based on three key weather variables: (1) daily dry bulb temperature (DryT), (2) daily global solar horizontal irradiation (GIRad) and (3) daily wind speed (WS). The equations for the selection of the most representative month presented by Eames *et al*. (2011) are as follows:

$$FS_{m,y} = \sum_{i=1}^{N_m} |CDF(i,m,y) - CDF(i,m,N_Y)| \,, \tag{2-11}$$

$$FS_{sum,m} = w_1 FS_m(DryT) + w_2 FS_m(GIRad) + w_3 FS_m(WS) \tag{2-12}$$

and

$$w_1 + w_2 + w_3 = 1, \tag{2-13}$$

where m is month (e.g. January), y is one of 30 years, i is day in month m, N_m is the length of month m (e.g. 31 for January), N_Y is overall years, $FS_{m,y}$ is the FS statistic for month m in year y, and $FS_{sum,m}$ is sum of three FS statistics with applying weighting factor w_1, w_2 and w_3. These weighting factors are dependent upon the relative importance of weather variable. For the CIBSE TRY, the value 1/3 was chosen since they were considered as equally important for the UK (Levermore and Parkinson, 2006).

The cumulative distribution functions (CDFs) of the three weather variables (i.e. DryT, GIRad and WS) of January for each individual year were compared to the CDFs of 30 Januaries from overall years. The January in year y which showed the least $FS_{sum,m}$ was considered as the most representative January. In the same manner, February, March and so on were selected. Subsequently, all twelve most representative months were assembled into a TRY. There are discontinuities occurred between the join of months as each month was drawn from different years. The mismatch between the join of two months can be smoothed using a simple statistical method presented by Levermore and Parkinson (2006). As mentioned before, the years with missing months could not be used as candidate years for the selection of the EWY. Hence, the EWY for some locations with a small number of complete observed years cannot represent long-term weather conditions. To the contrary, the creation of the TRY does not require complete year of weather data so that there would be long enough observed weather data that can be used. Therefore, the TRY is more reliable than the EWY with regard to representative of long term weather conditions though the TRY method is more complicated than the EWY method.

Hall *et al.* (1978) from Sandia National Laboratories have developed the Typical Meteorological Year (TMY) to be used in predicting the performance of solar energy systems, e.g. solar hot water system and solar thermal power plan. Since the dynamic building simulation requires the same type of hourly weather data as an input, the TMY also has been used to assess building energy performance. The TMY is a composite year which is composed of twelve the most typical months with each calendar month selected from at least ten years of observed hourly data. Though the TMY also adopted Finkelstein-Schafer (FS) statistic function (see equation 2-11) to select the most typical month, the TMY method is slightly different from the one used in the CIBSE TRY creation. The procedure for selecting the most typical month can be divided into two steps: the first step is to select five candidate years from long-term weather data using FS statistics for nine weather variables; and the second step is to apply persistence criterion to select one year from five candidate years (Hall *et al.*, 1978). For example, FS statistics of nine weather variables for each January of overall years (a number of observed historical years) were calculated. Sums of nine FS statistics with different weighting factors for the Januaries of overall years were ranked in order to select five candidate Januaries which showed the smallest sum of FS statistics. Then, the persistence of weather patterns: the consecutive days below the 33rd percentile of long-term (at least ten years) DryT, consecutive days above the 67th percentile of long-term DryT, and consecutive days below the 33rd percentile of a long-term GIRad were examined in order to select one from the five candidate Januaries. The TMY has been updated to the TMY2 and to the latest

TMY3 by the National Renewable Energy Laboratory[1] (NREL) using the same procedure but with modified weighting factors, different weather data set and different persistence criteria (Wilcox and Marion, 2008). The latest TMY3 for 239 U.S. locations were created based on the 30 years (1976 to 2005) of weather data while for another 950 U.S. locations based on the 15 years (1976 to 2005) of weather data. Hall *et al.* (1978) did not suggest a clear persistence criterion to apply to the final selection of the TMY. The persistence criteria applied to the TMY, TMY2 and TMY3 were all different. However, the method used for selecting the most typical month has been accepted worldwide.

In addition, BS EN ISO 15927-4:2005: (BSI, 2005) presents a slightly different approach to selecting the most representative month. January for example, three individual months with the smallest FS statistic for DryT, GIRad and humidity respectively are chosen as three candidate Januaries. Then, one of them with the mean WS showing the least deviation from the mean WS averaged over overall Januaries (i.e. all Januaries in observed historical years) is chosen. In the same manner, all of twelve months are chosen and concatenated to form a typical reference year.

The Weather Years for Energy Calculations (WYEC) also is a composite year but its approach is different from the one used to create the TRY and TMY. Each calendar month used to assemble WYEC was selected based on the monthly value (Crow, 1981). For example, the January with mean DryT closest to average DryT of overall Januaries was chosen. If the mean DryT of the chosen January ($DryT_c$) is higher than the mean DryT of overall Januaries ($DryT_{all}$) and the difference between them is greater than 0.1°C, days from different January which showed DryT close to but lower than the $DryT_{all}$ replaced the days of $DryT_c$ until the $DryT_c$ was within the 0.1°C of the $DryT_{all}$. The main weakness of this method is that other key weather variables such as solar radiation, wind speed and relative humidity were not considered when selecting the most representative month. Moreover, this method cannot exclude extreme events such as consecutive days of high or low daily DryT so that WYEC might fail to represent the typical long-term weather patterns. The NREL offers the latest revised WYEC files which are now known as WYEC version 2 (WYEC2) files. The WYEC data (available for 51 locations in the U.S. and Canada) and the TMY data (available for 26 locations in the U.S) were combined, then revised and improved by the NREL (Stoffel and Rymes, 1998) to form the 77 WYEC2 files. The drawbacks of the WYEC2, in fact, were inherited from the WYEC and the TMY.

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[1]National Renewable Energy Laboratory (NREL) is located in Golden, Colorado, United States. The research on renewable energy development from NREL is funded by U.S. DOE. Website: https://www.nrel.gov/about/golden.html

International Weather Years for Energy Calculations (IWEC) developed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers[2] (ASHRAE) is a composite year. ASHRAE intended to produce typical reference years, which is referred to as International Weather Years for Energy Calculations (IWEC), for locations beyond the United States and Canada using the Integrated Surface Database (ISD). The ISD includes weather data from more than 35,000 weather stations over the world. Thevenard and Brunger (2002) produced IWEC for 227 worldwide locations. Recently, the IWEC format has been modified and referred to as IWEC2 which are available for 3,012 locations outside the United States and Canada (Huang *et al.*, 2014). IWEC was created based on the similar method used in TMY but without concern on the persistence of weather patterns and with different weighting factors for the weather variables.

Morrison and Litvak (1999) selected the representative months based on a great number of simulation results. The month, for example, January, which showed the energy consumption closest to the average energy consumption of all historical Januaries was considered as the most representative January. The weighting factors on weather variables vary with different applications since GIRad is of more importance to solar systems while WS to wind farms (David Ferrari and Lee, 2008). Regarding application to building simulation, the weighting factors depend on the building types. For example, deep plan with low glazing ratio type is more sensitive to DryT whereas shallow-plan with high glazing ratio type is more sensitive to GIRad so that greater weights should be given to DryT and GIRad than other weather variables. However, it is not easy to clearly define the weighting factor for every weather variable which has more or less influence on the building simulation. The main advantage of Morrison and Litvak (1999)'s selection procedure is that it is unnecessary to define weighting factors. David Ferrari and Lee (2008), however, argued that this selection procedure is computationally expensive as a great number of different building models with the updated long-term weather data are required to ensure selecting the most representative month.

In summary, the composite year (e.g. TRY, TMY and IWEC which consist of the most representative month selected based on FS statistic function) is more popular than the continuous one (e.g. EWY, an entire year of hourly weather data). The composite year is created based on the monthly weather data while the continuous year is created based on the yearly weather data. As previously stated, a number of observed historical years with a few missing months, i.e.

[2] The American Society of Heating, Refrigerating and Air-Conditioning Engineers is an international organisation which publishes standards relating to building environment. Website: https://www.ashrae.org

incomplete years were discarded when creating EWY. Therefore, EWY would not represent the whole historical years. Approximately 15 to 20 years of complete observed weather data are required for selecting EWY. Continuous year approach is not robust for the locations with insufficient complete years of weather data. In practice, most of the weather stations rarely provide such perfect weather data (Levermore and Parkinson, 2006). However, incomplete years can be used to create the composite year. Therefore, the composite year approach is more applicable than the continuous year approach. In addition, selecting the most representative month based on FS statistic method is more advanced than based on mean value. As mentioned in the shortcoming of WYEC above, extreme values, e.g. hot spells and cold snap would stay in the WYEC since its component months were selected based on mean value alone. By contrast, FS statistics method is unlikely to select month with extreme values.

2.5.3. Summer reference year methods

The concept of typical reference year is inappropriate for the assessment of overheating risk during a hot summer. A year with warmer than typical summer which is referred to as summer reference year is essential when assessing the risk of overheating in the naturally ventilated buildings. Naturally ventilated buildings are vulnerable to the hot weather since the building itself, in addition to the occupants' adaptation behaviours, must guarantee safe and comfortable indoor environment during a hot summer without air-conditioning. Dynamic thermal simulation with summer reference year is a common exercise to evaluate the potential risk of overheating. There have been arguments on the approaches to the creation of summer reference years which are presented below.

a) CIBSE DSY

Levermore and Parkinson (2006) created the Design Summer Year (DSY) which was selected from 21 years or so (depending on the data availability) of weather data measured typically from 1983 to 2004 in the UK. Currently, CIBSE (CIBSE, 2013b) provides DSYs for fourteen UK sites. The daily mean DryT during all summer, i.e. April to September was calculated for each of 21 years. Then, 21 years were ranked in descending order of daily mean DryT. The year ranked in the third place was considered as DSY (Levermore and Parkinson, 2006). Since the DSY was selected based on the mean DryT over six months, it cannot be used to measure the severity of overheating. The DSY is a continuous year so that complete years of hourly weather data were required. The number of available complete years varies significantly from 6 to 21 across the fourteen UK locations. If any calendar month, for example, January is missing, the year was discarded (Levermore and Parkinson, 2006). Insufficient complete years of weather data for some locations such as Southampton and Swindon would affect the robustness of the DSY selection (Jentsch *et al.*, 2013). The DSYs were expected to deliver higher risk of overheating than the TRYs. However, Jentsch *et al.* (2013) found that the DSYs predicted lower risk of overheating than the TRYs did for Norwich, Nottingham and so on, which is the main limitation of DSYs. The British Atmospheric Data Centre (BADC) has updated the baseline weather data so that larger number of complete years (varies from 16 to 23) are available for each location. Jentsch *et al*. (2015) tried to overcome the limitation by using the updated complete years to select the DSYs. Nonetheless, it was found that the selected DSYs for Belfast, Manchester, Norwich and Newcastle remained the same suggesting that the limitation cannot be overcome by updating the baseline weather data (Jentsch *et al.*, 2015). Dynamic thermal simulation with all of 21 years showed that the DSY, which is the third warmest in terms of external mean summer temperature, cannot ensure the third warmest year in terms of indoor thermal discomfort (Kershaw *et al.*, 2010). It was also found that the DSY was likely to underestimate the overheating risk due to its simple selection method which is based on a single weather variable, i.e. DryT. Kershaw *et al.* (2010) suggested to consider various weather variables, such as cloud cover and wind speed, when selecting the DSY as they would have a great influence on indoor environment of, in particular, the naturally ventilated buildings with a high glazing ratio. Ji *et al.* (2016) proposed solar-air temperature averaged over April to September as an alternative metric to rank weather years from 1976 to 1995 for London. Solar-air temperature takes account of the combined effects of air temperature, solar radiation and wind speed. Ji *et al.* (2016) also tried to rank 20 years based on other metrics including averaged summer DryT used in CIBSE DSY selection, WCDH suggested by CIBSE TM49 (CIBSE, 2014) and accumulated degree hours over T_{comf} (ADHC). In total, 4000 dynamic thermal simulations have been carried out with all of 20 years which were then ranked based on the predicted indoor warmth. The warmth ranking of weather years did not consistently agree with the ranking of the predicted indoor warmth due to variations in the dwelling characteristics which have a great impact on the interaction between the outdoor and indoor environment (Ji *et al.*, 2016). That is, the occurrence or severity of overheating risk must not be solely judged by the warmth of weather years.

b) Summer Reference Years

Jentsch *et al.* (2015) developed the Summer Reference Years (SRY) to overcome the limitations in the simple DSY selection method. The TRY was mathematically adjusted to two years with near-extreme DryT and GIRad respectively (Jentsch *et al.*, 2015). Degree hours above 18°C during all summer were calculated for all of the available complete years which were then ranked in ascending order. The year with the 90th percentile degree hours above 18°C, which is equivalent to the year with the third highest degree hours, was defined as the year with near-extreme DryT. The DryT of the TRY (TRY_{DryT}) during all summer was adjusted to the DryT of the selected near-extreme year. In addition, the wet bulb temperature, WS and atmospheric pressure of the TRY during all summer were adjusted based on their correlations to the TRY_{DryT} as well as the scaling factor used in the TRY_{DryT} adjustment. The GIRad of the TRY (TRY_{GIRad}) was adjusted to an extreme year which was selected in a different way. The year with the 90th percentile mean daily GIRad was selected as one extreme candidate year. During all summer daily GIRad sums were calculated for each complete year to find out its ten sunniest days. All of the complete years were ranked in ascending order of their own ten sunniest days and then the 90th percentile year was selected as another extreme candidate year. Among the available complete years, the one which showed the least deviation from both extreme candidate years was used to shift direct horizontal irradiation component of TRY_{GIRad} to create the SRY. Jentsch *et al.* (2015) found that the SRY consistently showed greater overheating hours than the TRY did for all of fourteen UK locations. The weakness with this evaluation, however, is that overheating hours from non-realistic building model presented by CIBSE TM33 Test G8 (CIBSE, 2006) were used to compare the SRY with TRY. In addition, a moderate warm event year, i.e. probabilistic Design Summer Year No.1 (pDSY-1) which is same as the original CIBSE DSY developed by Levermore and Parkinson (2006), a longer extreme year, i.e. pDSY-2 and a more intense extreme year, i.e. pDSY-3 were suggested for London by CIBSE TM49 (CIBSE, 2014) in order to take account of duration and intense of warm spells. The pDSY-2 was selected based on the duration of the warm spell which is consecutive days with the temperature greater than the adaptive comfort temperature (T_{comf}) (see equation 2-14) for at least one hour while the pDSY-3 was selected based on the Weighted Cooling Degree Hours (WCDH) (see equation 2-9 and 2-10). Eames (2016) extended the methods and produced three alternative pDSYs for the fourteen UK locations. Besides WCDH, Static Weighted Cooling Degree Hours (SWCDH) and the Threshold Weighting Degree Hours (TWCDH) proposed by Eames (2016) were used to identify the extreme year. The SWCDH was calculated based on the similar equations used in WCDH calculation but static heat-related mortality threshold temperature, which is the 93rd percentile of year round 2-day mean temperature for the region (Armstrong *et al.*, 2011), was used instead of T_{comf}. The TWCDH was calculated in a similar way but taking account of both T_{comf} and regional static heat-related mortality threshold temperature. It is hard to define a representative building as various buildings have significantly different responses to climate conditions. Eames (2016) adopted a conceptual free running building which is presented by CIBSE TM49 (CIBSE, 2014) for the purpose of developing the summer reference years. The internal operative temperature is assumed to be equal to the external DryT in this building. Eames (2016) selected three pDSY based on (1) the duration of warm spells, (2) the intensity of WCDH, SWCDH and TWCDH (i.e. a total of WCDH/SWCDH/TWCDH divided by duration), and (3) assigned return periods of pDSYs which were estimated by using the Generalised Extreme Value distribution (Coles, 2013). One major drawback of Eames (2016)'s approach is that the effect of other important weather variables such as GIRad and WS were not taken into account.

c) Warm Reference Year (WRY) & eXtreme Meteorological Year (XMY)

Frank (2005) presented the Warm Reference Year (WRY) in order to predict the risk of overheating in the naturally ventilated domestic buildings during summer (May to September which is defined as summer season by the author). The WRY is a composite year created using 20 years (from 1984 to 2003) of observed weather data in Zurich-Kloten, Switzerland. Each calendar month in the WRY showed the highest mean monthly air temperature of all respective months in 20 years. The eXtreme Meteorological Year (XMY) was introduced by David Ferrari and Lee (2008) who suggested to combine the hottest summer (from November to March) with the coldest winter (May to September), selected from long-term weather data set, to form an XMY for Australia. The higher the temperatures during the cooling season, the higher score the month obtains, then the summer months with the highest score were considered as the hottest summer. The months of the coldest winter were selected using similar process; that is, the lower the temperatures during the heating season, the higher score the month obtains. For April and October, the months with more extremes but fewer averages compared to the respective months from the long-term weather data were selected. These individually selected months were concatenated to form a XMY. Both the WRY and XMY were composite years and failed to take account of GIRad, WS and so on which may have a great influence on thermal performance of buildings.

d) Untypical Meteorological Years (UMY)

Narowski *et al.* (2013) developed the three Untypical Meteorological Years (UMY) based on the WYEC2 but with three different sets of weighting factors on key weather variables. Four weather variables, i.e. minimum and maximum DryT, GIRad and maximum WS were given greater weights. For the UMY-v1 weights of 15% were put onto the minimum and maximum DryT and maximum WS while 37% was put onto the GIRad. The UMY-v2 was a year of extreme GIRad with the greatest weight of 55% while the UMY-v3 was a year of extreme WS with the greatest weight of 25%. The three UMYs were compared to the TMY2 and WYEC2 (i.e. the most averaged year) in terms of cooling energy demand and hours above 27°C averaged from a few simple building models including two thermal mass, with and without horizontal overhang (1 m), and four building orientations but the same geometry. Narowski *et al.* (2013) found that the UMY-v3 showed the most cooling energy demand as well as hours above 27°C of all five weather years but none of the UMYs was appropriate to predict peak cooling energy demand. Unfortunately, it was found that the TMY2 and WYEC2 showed the higher peak cooling energy demand than all types of the UMYs. This indicated that the UMYs suggested by Narowski *et al.* (2013) would fail to measure the severity of overheating. In addition, the investigation into the UMYs for use in overheating risk assessment via the comparison between the UMYs and the TMY2/WYEC2 would have been more comprehensive if various building geometries were taken into consideration.

2.5.4. Future weather data generation

Future weather data is necessary to create future weather files for use in building simulations. This subsection describes two methods: one is morphing method, i.e. mathematically transforming observed weather data using climate change projections (Belcher *et al.*, 2005), and the other is producing future synthetic weather data using UKCP09 weather generator (Kilsby *et al.*, 2007; Jones *et al.*, 2010).

a) Morphing method

Belcher *et al.* (2005) have constructed future weather data which can be used in the dynamic thermal simulation. The climate change projections from a global or a regional climate model have been used to morph observed weather data, i.e. baseline data. The baseline data was averaged over a 30-year period of historical weather data (typically from 1961 to 1990), which were recommended by the World Meteorological Organization, in order to represent current climate. The three morphing mechanisms are: (1) shifting the baseline data based on the absolute change in monthly mean, (2) stretching the baseline data based on the relative change in monthly mean, and (3) combination of shifting and stretching. The UK regional climate change projections, i.e. UK Climate Impacts Programme (UKCIP02) which has been replaced by UKCP09 (Jones *et al.*, 2010), could produce mean monthly climate changes for the weather variables at horizontal resolution of 50 km for three decadal steps (i.e. the 2020s, 2050s and 2080s) under four emission scenarios (from low to high SRES B1, SRES B2, SRES A2, SRES A1F1 (IPCC, 2000)). UKCIP02 climate projections involved two types of climate changes: one is absolute change to the mean, and the other is fractional change depending on the weather variables. For example, UKCIP02 offered absolute changes to the air temperatures, monthly mean solar irradiance, relative humidity, atmospheric pressure and so on, while relative changes (%) for total precipitation rate and wind speed etc. Given these UKCIP02 climate changes and the characteristics of weather variables, one of the three morphing mechanisms was determined. For example, given absolute changes, a shift was directly applied to the baseline atmospheric pressure; while given relative changes, the future wind speed was morphed by stretching the baseline data. Sometimes, scaling factors were calculated for the weather variables that required stretching as they were provided absolute changes instead of relative changes. For example, solar irradiance needs to be stretched rather than shifted otherwise there might be sunshine in the night. However, UKCIP02 offered an absolute change to monthly mean solar irradiance so that its scaling factor should be calculated. Belcher *et al.* (2005) suggested a method to calculate the scaling factor using the absolute change and the monthly mean from baseline data. For DryT, the combination of a shift and a stretch was used. In addition to shifting the mean temperature from baseline, the diurnal range was stretched by the calculated scaling factor. Belcher *et al.* (2005) morphed the mean DryT and the diurnal cycle but maximum and minimum DryT, which might result in lack of a stretch in the high summer temperatures; consequently, dynamic thermal simulation with morphed future weather files might underestimate overheating hours (i.e. hours above 28°C) and WCDH (see equations 9 and 10) (Eames *et al.*, 2012b). One of the advantages of the morphed future weather year, however, is that the physically realistic weather sequences were preserved. Notwithstanding, the morphing method cannot consider the potential changes in characteristics and variability of future climate (Belcher *et al.*, 2005). Belcher *et al.* (2005) stated that the application of the morphing method was limited to a small number of locations in practice since the period of historical weather data should be equal to the baseline period (typically from 1961 to 1990) used by global or regional climate models. In fact, the problem for lack of the baseline data has been solved since the UKCP09 WG (Kilsby *et al.*, 2007; Jones *et al.*, 2010) can provide the 100 sets of 30-year baseline weather (i.e. control year) data at 5 km by 5km spatial resolution across the UK. The control year data has been validated with the observed weather data.

b) UKCP09 Weather Generator

The UKCP09 climate projections are the fifth generation of climate change predictions for the UK. The Met Office has made a great contribution to the work based on the latest and the most advanced climate science. Compared to the previous generation of climate change projection from UK Climate Impacts Programme (UKCIP02) which offered deterministic projections, UKCP09 makes the climate modelling uncertainty more transparent by providing the range of probabilities in the future climate projections. Thus, the UKCP09 probabilistic climate changes allow users to make different decisions based on potential risks to address the impacts of climate change. Furthermore, the UKCP09 provides future climate change at 25 km by 25 km horizontal resolution across the UK which is four times as high as the UKCIP02's resolution. UKCP09 projections are based on the High (SRES A1FI), Medium (SRES A1B) and Low (SRES B1) emission scenarios which are significantly important for modelling of future climate change.

The UKCP09 Weather Generator (UKCP09 WG) (Kilsby *et al.*, 2007) that is based on stochastic rainfall model was developed by the University of Newcastle. The UKCP09 WG takes precipitation sequence as the primary variable whereas other variables are calculated from it by maintaining the inter-variable relationships with rainfall. The UKCP09 WG can produce both baseline (from 1961 to 1990) and future (from the 2020s to 2080s) daily and hourly weather data under three different emission scenarios which are consistent with those used for UKCP09 probabilistic climate projection. Perry and Hollis (2005) spatially interpolated the weather data from sparse network of weather stations and produced data set at 5km by 5km grid resolution for the UK. The gridded data set was used to calibrate the UKCP09 WG. Hence, the baseline data produced by UKCP09 WG agrees well with the observed weather data. The future daily and hourly weather data are created by perturbing the baseline data with UKCP09 climate change projection. Though the resolution of the UKCP09 WG outputs is 5 km by 5 km, the underlying climate change information is no further than 25 km by 25 km horizontal resolution of UKCP09 climate change projections. Each run of the UKCP09 WG can produce 100 sets of 30-year period weather data for both baseline period (i.e. control year) and user defined future period. According to the user-defined future time period under chosen emission scenario, UKCP09 creates 10,000 probabilistic climate change projections to form probability density distribution. Then, one randomly selected projection is incorporated into each set of 30-year period baseline weather data. In total, 100 projections are incorporated into the 100 sets of 30-year period baseline weather data. In the meantime, the hourly weather data are derived by disaggregating the daily weather data. The UKCP09 WG provides nine weather variables for the daily basis and seven weather variables for the hourly basis as presented in Table 2-9.

Table 2-9. UKCP09 weather generator outputs (this table is copied from my own work (Liu et al., 2016) which has been published in a journal).

Emission scenarios	Time slices	Output variables	
		Daily data	**Hourly data**
1. Low (SRES B1)	Control year: 1961 to 1990	1. Mean total daily precipitation (mm)	1. Mean total hourly precipitation rate (mm)
2. Medium (SRES A1B)	Future year:	2. Minimum daily temperature (°C)	2. Mean hourly temperature (°C)
3. High (SRES A1FI)	1. 2020s: 2010 to 2039	3. Maximum daily temperature (°C)	3. Vapour pressure (hPa)
	2. 2030s: 2020 to 2049	4. Vapour pressure (hPa)	4. Relative humidity (%)
	3. 2040s: 2030 to 2059	5. Relative humidity (%)	5. Sunshine hours (hr)
	4. 2050s: 2040 to 2069	6. Sunshine hours (hr)	6. Direct irradiation (Wh/m^2)
	5. 2060s: 2050 to 2079	7. Diffuse irradiation (kWh/m^2)	7. Diffuse irradiation (Wh/m^2)
	6. 2070s: 2060 to 2089	8. Direct irradiation (kWh/m^2)	
	7. 2080s: 2070 to 2099	9. Potential evapotranspiration (mm/day)	

However, the number of the weather variables is less than required in constructing the building simulation weather files. For example, the UKCP09 WG cannot produce wind speed and direction, atmospheric pressure and cloud cover which are essential for building simulation weather files. Some of them can be deduced from the outputs of the UKCP09 WG. For example, the cloud cover which is correlated to the solar radiation can be simply acquired from hourly sunshine fraction. For wind speed which is significantly important for natural ventilated building modelling, it takes rather complex steps to deduce it from outputs of the UKCP09 WG. In order to taking advantages of the UKCP09 WG to create the building simulation weather files, missing weather variables should be calculated. In addition to the missing weather variables, solar radiation needs to be recalculated as Eames *et al.* (2012b) found that the hourly direct and diffuse solar radiations from the UKCP09 WG were not in well agreement with observed weather. Like other weather variables, the daily solar radiations were calculated from total daily sunshine duration; then, the hourly values were derived from disaggregating the daily values based on the inter-variable relationships from observation. That is, the hourly solar radiations were created based on statistical rather than physical basis, which might lead to the significant errors. For instance, the direct solar radiations from the UKCP09 WG are on average higher than diffuse solar radiation before sun rise and after sun set, which is impossible in the realistic conditions (Eames *et al*., 2012). The methodologies for calculating solar radiations as well as the missing weather variables can be found in Table 3-2. The UKCP09 WG only works for the UK whereas the morphing method can be used to create future weather data for worldwide locations. Due to the lack of long period (typically from 1961 to 1990) of observed weather data, missing weather variables and a low spatial resolution of weather stations, the use of morphing method in practice is applicable to a limited number of locations without such issues.

2.5.5. Future summer reference years

The methods used to create future summer reference years were different from those used to create current summer reference years due to the difference between the future and the observed historical weather data set.

a) Future CIBSE DSY

Morphing method has been used to produce future building simulation weather files. For example, Climate Change Weather File Generator (CCWeatherGen) developed by University of Southampton (Jentsch, 2012) uses UKCIP02 deterministic climate change projections to morph the CIBSE TRYs and DSYs to produce future TRYs and DSYs. The future DSYs, therefore, inherited the shortcomings of the simple DSY selection method.

Alternative approaches have been developed since the synthetic future weather data was available from the UKCP09 WG. Given future time slice and emission scenario, each run of the UKCP09 WG produces 100 sets of 30-year long weather data; that is, randomly selected 100 UKCP09 probabilistic climate projections are incorporated into the baseline (i.e. control year from 1961 to 1990) weather data. Unlike future DSYs, which were created via morphing around 21-year long observed weather data with one set of deterministic climate projections offered by the UKCIP02, the following future summer reference years were constructed based on the outputs from UKCP09 WG.

b) Future probabilistic DSY

Eames *et al.* (2011) have developed future probabilistic Design Summer Year (pDSY) using the UKCP09 WG outputs. As mentioned before, each run of the UKCP09 WG produces 100 sets of 30-year long weather data for a location. Eames *et al.* (2011) ranked each set of 30 years in ascending order of mean air temperature during April to Septembers. One DSY was selected from each set of 30-year long weather data using the CIBSE DSY selection method. Due to the longer period of weather data compared to the typically 21-year baseline data used for the CIBSE DSY selection, rather than the third warmest, the fourth warmest year was chosen as the DSY. In the first place, 100 DSYs could be selected from 100 sets of 30-year long future weather data. In the second place, each calendar month (e.g. January) of 100 DSYs was ranked in ascending order of mean monthly air temperature. Then twelve calendar months with the same percentile were concatenated to form the future probabilistic DSY; for example, the 50th percentile January, February and so on were concatenated to form the 50th percentile DSY. Regarding mean monthly temperature the high percentile DSYs was consistently higher than the low percentile DSYs whereas other weather variables such as total solar radiation, relative humidity and wind speed were failed to show the consistent trend as the whole selection procedure was based on the mean monthly temperature for simplicity (Eames *et al*., 2011).

c) Probabilistic DSY and single DSY

Eames *et al.* (2011) proposed composite DSYs while Smith and Hanby (2012) suggested continuous years by maintaining the method used for the CIBSE DSY selection. Smith and Hanby (2012) tried to develop the probabilistic DSYs (pDSYs) and single DSY based on two change factor sampling methods (i.e. random sampling and percentile sampling) and two ways for treating the UKCP09 WG outputs as illustrated in Figure 2-7. The probabilistic elements for the A type pDSY were defined after running the UKCP09 WG, i.e. when ordering the 100 DSYs, while that for C and D type pDSY were determined before running the UKCP09 WG. Multi-run of the UKCP09 WG is required to produce C or D type of probabilistic DSYs, whereas a single run of the UKCP09 WG is enough to produce an entire A type pDSYs, i.e. from the 1st pDSY to 100th pDSY. Though both B and D type treated the 3,000 years as one set during DSY selection, the B type is a single DSY while D type is pDSY which includes the percentile element defined by percentile sampling at the initial stage. As shown in Table 2-9, the UKCP09 WG is able to produce control year (from 1961 to 1990) weather data representing current climate. Smith and Hanby (2012) created the B type DSY using control year data generated by the UKCP09 WG and compared it with the DSY created using the observed weather data for three UK locations including London, Manchester and Edinburgh. It was found that the difference in the temperature averaged over April to September between them was less than 0.5°C for all of three locations, indicating that it is suitable to use the UKCP09 WG outputs to create DSYs. Smith and Hanby (2012) also found that the 50th DSYs (i.e. A type pDSY) created using future weather data from UKCP09 WG were slightly warmer than the morphed future DSYs which included UKCIP02 deterministic climate projection. Furthermore, A type pDSY showed slightly higher temperature (averaged over April to September) than other types while the differences in WCDH between them were significantly high (Smith and Hanby, 2012). Therefore, A type pDSY is more appropriate to measure the severity of warmth than other types. Due to the random sampling method single run of the UKCP09 WG can produce multiple A type pDSYs. Hence, the A type pDSY showed advantages over other types. Smith and Hanby (2012), in fact, did not try to overcome the issue with the simple CIBSE DSY selection method so that all four types of DSYs proposed have the same shortcomings of the CIBSE DSYs.

d) Design Reference Year

Watkins *et al*. (2012) presented the design reference year (DRY) using the UKCP09 WG outputs. The DRY is a composite year consisting of extreme months, each selected from different years. For example, the monthly mean air temperature was calculated for each July of 3,000 years (i.e. 100 sets of 30-year long weather data) from each run of the UKCP09 WG. The 3,000 years were ranked in ascending order based on the mean temperature in July as shown in Figure 2-8. The authors extracted 20 years around the centre of the year that corresponds to the percentile of interest (e.g. 87.5 percentile illustrated in Figure 2-8); in total, 21 years were sampled. The higher percentile was chosen as a central sampling point, the more extreme months the DRY would contain and vice versa. The FS statistic (see equation 2-11 and 2-12 which were used to select the most representative calendar month) was calculated for each of 21 years based on three weather variables: (1) daily mean temperatures, (2) total daily solar irradiation and (3) relative humidity. Then, the 21 years were ranked based on the three weather variables respectively to form three sets of the order list. Based on the desceding order of sum of three ranks (each from one of these order lists), the first three years were selected. After then, July in one of the three years, for example, which showed the closest mean monthly wind speed to the one averaged over all 21 years was selected. In the same manner, all twelve calendar months were selected and concatenated to form the DRY. Watkins *et al*. (2012) presented three DRYs, each being created based on daily mean temperature, relative humidity and total solar irradiation respectively for use in different types of buildings. According to the authors, the use of three DRYs should be dependant upon the building types as different buildings have different sensitivities to weather variables. Though the authors aimed to develop new summer reference years which could be used to evaluate the resilience of building designs under an extreme weather condition, they have made no attempts to compare the DRYs with the typical reference years such as the TRYs to justify the robustness of the DRY approach. It is significantly important to examine if the DRYs are consistently warmer than the TRYs during summer in order to address the main issue with the simple CIBSE DSY selection method mentioned in subsection 2.5.3.

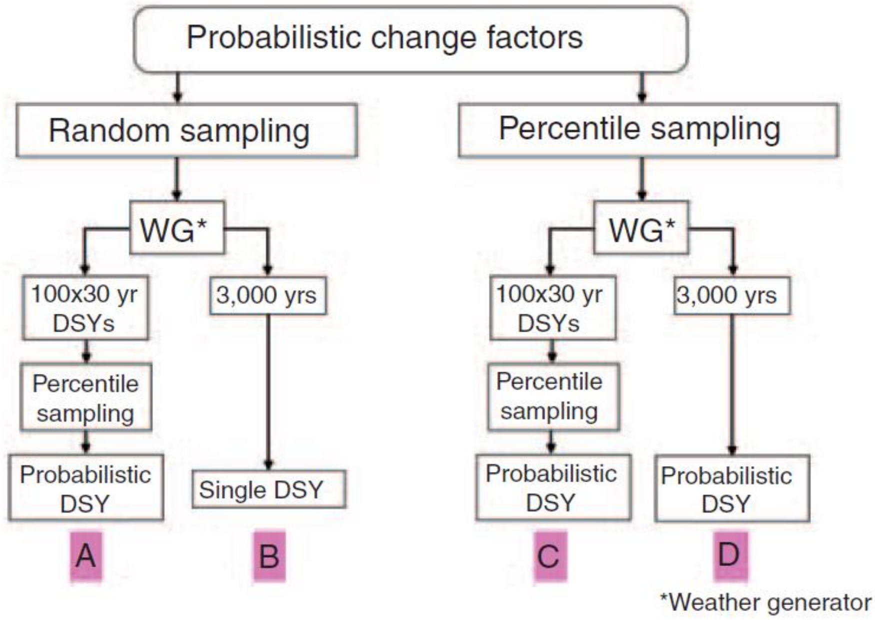


Figure 2-7. The selection procedure for DSY selection (source: Smith and Hanby (2012)).

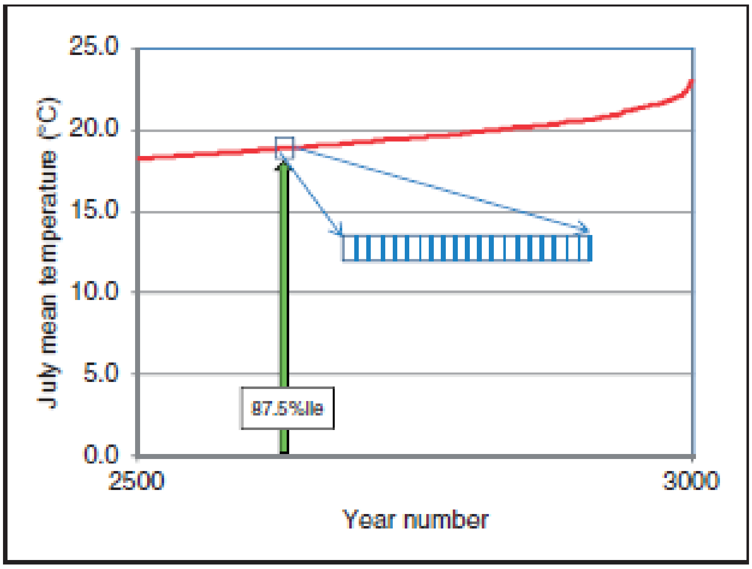


Figure 2-8. Ascending order of 3,000 years based on the July mean temperature. The blue box represent 21 sampling years with the 87.5th percentile year as a centre (source: Watkins et al. (2012)).

2.6. Overheating risk assessment

This section reviews the approaches to the assessment of overheating risk in free-running buildings (i.e. buildings that are not heated or cooled) during summer in the UK. Previous studies on the assessment of overheating risk under the current and possible future climates are stated in subsection 2.6.1 and 2.6.2 respectively. In addition, spatial variation in overheating risk is discussed in subsection 2.6.3. The main findings from previous research on overheating risk are summarised in subsection 2.6.4.

2.6.1. Overheating risk under the current climate

Household interview, monitoring internal temperature, thermal simulations with summer years, and so on have been used to investigate the risk of overheating.

a) Household interview

Household interview, i.e. asking residents whether they feel uncomfortably hot or not is a common way to measure subjective overheating under the current climate condition. For example, the EHS and EFUS (mentioned in subsection 2.4.1) included subjective overheating measurement for English housing stock at a national scale during summer. The Household interview was conducted by professional surveyors. Different housing surveys use different questionnaires which might lead to different results. According to the EHS Headline Report 2015-16 (DCLG, 2017), for instance, there were 7% of people felt that at least one of their rooms were uncomfortably hot while the EFUS (DECC, 2013) reported 20%. Furthermore, EHS (DCLG, 2017) reported that detached houses were more likely to overheat compared to terraced houses while EFUS (DECC, 2013) found that the small terraced houses were at a slightly higher risk of overheating than the detached houses.

b) Monitoring

In addition to the results from household interview, EFUS (DECC, 2013) included further thermal comfort analysis based on the monitored internal temperatures in 823 households for one year. The mean internal summer temperatures (i.e. living room and main bedroom temperatures averaged over June to August in 2011) in the households that reported overheating were significantly higher than those did not; meanwhile the mean internal summer temperatures that households felt discomfort were correlated to the threshold temperatures for medium level (see

Table 2-7) of overheating risk suggested by SAP (BRE, 2012). In addition, the people living in the dwellings with a SAP rating (i.e. energy efficient rating) greater than 70 faced a higher risk of overheating than those living in the dwellings with lower SAP ratings; that is, the higher the building energy efficiency the higher the risk of overheating. Beizaee *et al.* (2013) assessed the risk of overheating for English housing stock at a national scale but mainly based on the living room and bedroom temperatures recorded for 193 free-running dwellings during 41 days in summer (22nd July to 31st August in 2007). Both static criteria presented in CIBSE Guide A (CIBSE, 2006a) and the adaptive criteria recommended by BS EN15251 (BSI, 2007) were used to assess the internal temperatures for arbitrarily but reasonably defined occupied hours (08:00 to 22:00 for the living room and 23:00 to 07:00 for the main bedroom). Static criteria were used to calculate the overheating hours (i.e. hours above the static threshold summertime temperatures) while the adaptive criteria were used to calculate the occupied hours beyond the thermal comfort boundaries defined by category II and III respectively (see Figure 2-5 and Table 2-4). It was found that most of the dwellings were uncomfortably cool based on the BS EN15251 adaptive criteria. Though the monitored period was a cool summer 4% of the living rooms and 21% of the main bedrooms exceeded the static threshold summertime temperatures recommended by CIBSE Guide A static criteria. Note that the proportion of overheated main bedrooms was significantly greater than that of overheated living rooms though there was a small difference between the temperature averaged over all the bedrooms and that averaged over all the living rooms (Beizaee *et al.*, 2013). According to the CIBSE Guide A static criteria, the summertime threshold temperature for the bedroom is 2°C lower than that for the living room, which Beizaee *et al.* (2013) considered as the main reason for the significant difference in overheating between them. The authors also found that fewer bedrooms in the detached houses overheated compared to other dwelling types due to the greater external wall area from which houses can release substantial internal heat. However, the authors failed to explain why there was a surprisingly high proportion of bedrooms in the end-terraced houses under the risk of overheating. K.J.Lomas and T.Kane (2013) monitored living room and the main bedroom temperatures only for a city located in central England. The monitored period was from 1st July to 31st August in 2009 which was also a cool summer but including a hot spell. The authors used the similar method presented by Beizaee *et al.* (2013), i.e. assuming the same occupied hours for the living room and the main bedroom, and using the same static and adaptive criteria (i.e. CIBSE Guide A static criteria (CIBSE, 2006a) and BS EN15251 adaptive criteria (BSI, 2007)) when analysing the indoor thermal comfort. Interestingly, there were a large number of houses showing internal temperatures above static summertime threshold temperature for more than 1% of occupied hours, i.e. the static criteria while a great number of houses presenting indoor temperature below the lower limits defined by the category II and III for more than 5%, i.e. BS EN15251 adaptive comfort criteria (K.J.Lomas and T.Kane, 2013). Due to the hot spell occurred during the monitored period, on one hand, the indoor temperatures exceeded the static summertime threshold temperature for most of the occupied hours during the hot spell (note that 15% of bedrooms overheat more than 30% of occupied hours due to the hot spell), thereby the overall overheating hours during the whole monitored period, despite cool summer for the rest of monitoring period, could still exceed 1% of the occupied hours. Due to the cool summer during most of the monitoring period, on the other hand, the houses in the case study city generally showed uncomfortably cool, which is consistent with findings from Beizaee *et al.* (2013). Though Beizaee *et al.* (2013) and Lomas and Kane (2013) presented slightly different results, for instance, different percentages of overheated living rooms and the main bedrooms due to the sampling bias, they drew the same conclusions that living rooms in the flats, especially in the top floor flats, are more likely to be at a high risk of overheating than other dwelling types due to the smaller external wall area; old dwellings (pre-1919), detached houses and dwellings with solid wall construction are more likely to be uncomfortably cool compared to the modern dwellings (post-1990) and dwellings with cavity wall construction due to the greater external wall area and poorer insulation.

c) Thermal simulation

Building designers perform thermal simulations to understand the interaction between the buildings and the external environment. Summer reference years (described in subsection 2.5.3) have been used in dynamic thermal simulation to assess the risk of overheating. As mentioned in section 2.3, there are inevitably gaps between the thermal simulation results and the real thermal performance of buildings due to the lack of information required for accurate thermal modelling, uncertainties in occupants' behaviours, imperfect simulation engines, and so on. Thermal simulation, however, is preferable to other methods when analysing the relative importance of building characteristics and environmental factors on indoor thermal comfort. In addition, various thermal comfort assessment criteria including static and adaptive criteria have been incorporated into the dynamic simulation packages, such as EnergyPlus and IES <VE>, which enables building practitioners to obtain more comprehensive results with less effort. It is efficient to test the building characteristics and passive adaptive interventions to find out the best solution to reduce the risk of overheating. For example, Mavrogianni *et al.* (2012) carried out dynamic thermal simulations with a current CIBSE DSY for fifteen London dwelling archetypes in order to find out the influence of built form and age on the internal air temperature. The occurrence of high internal temperature increased with floor level; for instance, top floor flats were warmer than the middle floor flats; and many of the dwellings built between 1914 and 1945 showed high mean and maximum living room temperatures. The authors stated that the built form and age could indicate the risk of overheating. In addition, the effect of retrofitting wall, floor, roof/loft and window has been evaluated via dynamic thermal simulation. The combination of roof/loft and window insulations resulted in decrease of 0.76°C and 1.3°C for the mean and maximum daytime living room temperatures respectively; on the contrary, wall and floor insulations led to an increase in the mean and maximum daytime living room temperatures by 0.38°C and 0.61°C respectively (Mavrogianni *et al.*, 2012). This indicated that retrofitting dwellings should be carefully considered rather than merely focusing on improvement of building energy efficiency to reduce the carbon emission. Regarding variation in overheating risk for London housing stocks, Mavrogianni *et al.* (2012) drew an important conclusion that the variation within the dwellings of the same type was greater than the variation between the different dwelling types, which was supported by Liu *et al.* (2017). Porritt *et al.* (2012) evaluated the effectiveness as well as the cost of different passive interventions (e.g. external and internal wall insulations, solar reflective coating, shading device installation, night-time ventilation) via dynamic thermal simulation. Degree hours over 26°C and 28°C for the bedrooms and the living rooms respectively were calculated for the most typical end and mid terraced houses in London during the 2003 European heat wave which lasted nine days from 4th to 12th in August. It was found that the external wall insulation was more effective than the internal wall insulation which undesirably increased the degree hours in some cases due to restricted radiative cooling via thermal mass and trapped internal gains. For example, external wall insulation reduced degree hours up to 50% for bedrooms and at least 20% for living rooms; in contrast, internal wall insulation resulted in increase of 14% and 21% degree hours for the bedrooms and living rooms respectively. Thus, the internal wall insulation should be used with caution as it might increase the risk of overheating, which was also in accord with Mavrogianni *et al.* (2012)'s findings. Porritt *et al.* (2012) found that the solar reflective coating was the most effective intervention for the end-terraced houses, with over 50% and 60% reduction in degree hours for the bedrooms and the living rooms respectively. Besides, the internal shading devices (e.g. blinds and curtains) were found to be less effective than the external ones (e.g. overhang and shutters) as the solar radiation is converted to long wave radiation, i.e. heat once it trespasses. The building orientation and the occupied hours had a substantial influence on overheating risk as they determined the exposed hours to solar radiation (Porritt *et al.*, 2010; Porritt *et al.*, 2012). As such, shading devices were more effective in reducing solar gains when the living rooms and the main bedrooms were facing south. Heating energy demand in winter would be increased due to the reduced solar gains by solar reflective coating and fixed shading device (e.g. overhang). Interestingly, Porritt *et al.* (2012) found that loft insulation showed benefit in reducing not only overheating risk but also space heating demand for bedrooms. In addition, night ventilation is an effective way of reducing bedroom temperature. It was found that night ventilation had a positive impact on reducing the risk of overheating for the building as a whole as night ventilation was beneficial to cooling the thermal mass (Porritt *et al.*, 2012). In addition, the applicability and cost of the interventions should be considered. As Porritt *et al.* (2012) stated that low-e triple glazing and external shutters are more effective but more expensive than double glazing and internal blinds; overhang and external wall insulation might affect the external appearance; night ventilation might be restricted due to the security, noise, air pollution and so on. Based on the dynamic thermal simulations with six different regional weather files for the same dwelling archetypes Taylor *et al.* (2014) found that different regional climates had a significant influence on the relative risk of overheating between dwelling types indicating that the results for a specific region should not be applied to other regions generically. Taylor *et al.* (2014) investigated the impact of individual weather variable (e.g. DryT, cloud cover, WS, GIRad) on daily maximum temperatures in the living rooms (T_{max}^{daily}) of different dwelling types. It was found that DryT and T_{max}^{daily} were most closely related, then followed by GIRad; both had a greater impact on T_{max}^{daily} of semi-detached houses, bungalows and top floor flats than that of other dwelling types. In contrast, cloud cover reduced T_{max}^{daily} and its influence on flats were greater than detached and semi-detached houses.

d) Other methods

Wright *et al*. (2005) measured internal temperature for four houses (i.e. two detached and two semi-detached houses) in Manchester and five houses (i.e. four flats and one semi-detached house) in London during the heat wave in August 2003. Wright *et al*. (2005) developed a regression model, i.e. a correlation between the daily internal temperature and the daily historic temperature (T_h^n) which can be calculated as follows:

$$T_h^n = \alpha \cdot T^n + (1-\alpha) \cdot T_h^{n-1}\ , \qquad (2\text{-}15)$$

where T^n is the daily external temperature on day number n, T_h^{n-1} is the historic temperature of the preceding day and α is a constant greater than zero but no more than one. Due to the time lag effect of thermal mass using T_h^n was more appropriate than directly using T^n when developing the correlation between the external and internal temperatures (Wright *et al.*, 2005). In order to maximise the R^2 to figure out the best relationship between the T_h^n and the measured daily internal temperature, the authors optimised α to adjust T_h^n. The slopes of linear regressions for the different room types in the same house were different. α ranged from 0.3 (heavy weight construction) to 0.8 (light weight construction) according to the analysis of all of nine dwellings. Therefore, the regression model should be created for each room, which is, however, simple as only two variables, i.e. the daily internal and external temperatures measured for a short period were required. Though the regression model for each room was developed based on a short period of measurement R^2 was greater than 0.9 for most of the rooms (Wright *et al*., 2005). By assuming the linear relationship unchanged, people are able to predict the internal temperature for a long period or even a possible future climate. This approach, however, should be used with caution as the linear relationship is likely to change due to the changing climate. According to the thermal comfort assessment based on the CIBSE Guide A static criteria (CIBSE, 2006a) and ASHRAE adaptive criterion with 90% acceptability (i.e. narrower band illustrated in Figure 2-5), all of the monitored houses failed to provide comfortable indoor environment during the hot spell (Wright *et al*., 2005). The authors recommended to pay attention to the regional climate when designing new buildings and to use air conditioning to avoid heat-related deaths during such hot spell. Based on thermal comfort survey in eight free-running office buildings conducted from the 13th of June to the 27th of September in 2006 (heat wave occurred during this period), Robinson and Haldi (2008) found that the participants were able to be tolerant of an occasional hot event but an accumulation of heat stress. Robinson and Haldi (2008) made an analogy between the human thermal tolerance against the accumulation of heat stimuli and an electrical capacitor, i.e. Resistor and Capacitor circuit (RC circuit). In order to solve the issue that using the static threshold summertime temperatures for judging the overheating was arbitrary, the authors proposed probability of overheating P which can be calculated as follows:

$$P = 1 - T\,, \tag{2-15}$$

where T is the thermal tolerance to the overheating stimuli (e.g. degree hours above reference temperature 25°C). T, varying between 0 and 1, is discharged (decreasing) during consecutive warm days while recharged (increasing) if followed by a cool period. The detailed mathematical equations for calculating T can be found in the paper written by Robinson and Haldi (2008). There were two coefficients empirically determined by the authors for calculating charging and discharging time respectively. Further study on the coefficients is needed as both vary with the climate type (Robinson and Haldi, 2008). As mentioned in the paper there were several problems with this approach. For example, the influence of other thermally related weather variables (e.g.

solar radiation, wind speed and relative humidity), personal factors (i.e. clothing insulation and metabolic rate) and occupants' adaptability (e.g. opening windows or closing shutters) were not taken into account. The physical and psychological adaptive processes, however, could be taken into account by adjusting the coefficients used in T calculation (Robinson and Haldi, 2008).

2.6.2. Overheating risk under a changing climate

A significant increase in the risk of overheating has been predicted for the possible future climate scenarios (Gupta and Gregg, 2013; Gupta and Gregg, 2012; Kershaw *et al.*, 2011; Jentsch *et al.*, 2008; Gul *et al.*, 2012; Demanuele *et al.*, 2012; McLeod *et al.*, 2013; Patidar *et al.*, 2011; Taylor *et al.*, 2014; Jenkins *et al.*, 2014). It is, therefore, crucial to design or renovate buildings to adapt to changing climates. Apart from household interview and monitoring, as expected, the approaches to the assessment of current overheating risk can be used to predict future overheating risk with future climate scenarios. Alternative approaches have been proposed to deal with the uncertainty in the future climate projections which would affect the estimation of overheating risk.

a) Dynamic thermal simulation with reference years warmer than the area of interest

Reference years derived from warmer than the study areas could be used to represent the warming climate projected for the study areas. The warmer years had to be used when the future weather years were unavailable. For example, Milan and Rome climates (relatively warm regions) were used to represent two possible UK climates (relatively cool regions) in the 2050s projected under the low and high emission scenarios respectively (Gaterell and McEvoy, 2005). The issue with this approach is that the weather file obtained from a warmer area could represent the rising temperature but other thermally related weather variables such as sunshine duration, wind and humidity for the area of interest. These weather variables might be very different due to the different latitude, longitude, altitude, topology, and so on. The issue has been overcome since the advent of future weather data (as described in subsection 2.5.4) which incorporated regional climate change projections and has been used to construct the future weather years for use in dynamic thermal simulation.

b) Dynamic thermal simulation with future reference years

Gupta and Gregg (2012) carried out the dynamic thermal simulation with future reference years. The authors found that overheating risk for English housing stock estimated with possible future climate scenarios, for instance, the 2080s under high emission scenario at 90% probability (i.e.

near-extreme climate scenario), cannot be entirely eliminated by any combination of passive adaptation measures. They also identified that external wall insulation was more effective than the internal wall insulation, which is in line with the findings from Porritt *et al.* (2012) and Mavrogianni *et al.* (2012). The louvred shading on glazing was found to be more effective than other passive adaptation measures such as fabric insulation, high surface albedo, high exposed thermal mass, and retrofitting windows with low-E double glazing. As the solar gains are likely to increase in the future due to the rising solar radiation in south England the shading and high albedo surface would be increasingly effective in reducing the risk of overheating (Gupta and Gregg, 2012). As an expansion to the previous research Gupta and Gregg (2013) predicted the overheating risk for three cities in the UK using thermal models of suburban houses (84% population living in suburban area) and future probabilistic Design Summer Years (i.e. the 90th percentile DSYs for the 2030s and 2050s under high emission scenario representing the year with near-extreme hot summer) created by Eames *et al.* (2011). They put emphasis on the importance of passive adaptations which could effectively mitigate the influence of warming climate on indoor thermal comfort. Most of the suburban houses showed that the overheating hours above the upper limit adaptive comfort temperature, defined by category II in BS EN adaptive comfort model (BSI, 2007), exceeded 5% of occupied hours during summer (from May to September). By the 2050s, even the combination of the most effective passive adaptations would not keep comfortable environment for the people, especially for the vulnerable group, living in South East of England; hence, the active cooling is required (Gupta and Gregg, 2013). This prediction is more critical compared with the previous work (Gupta and Gregg, 2012) which suggested the passive adaptations would not be capable of eliminating entire overheating risk by the 2080s.

c) Static thermal simulation

Tillson *et al.* (2013) estimated the current and future overheating risk for the English housing stocks using SAP method (BRE, 2012), i.e. static thermal simulation with housing data offered by EHS (DCLG, 2011b). As described in subsection 2.3.1, SAP method uses typical climate data (i.e. monthly mean external temperature, mean global solar irradiance and wind speed) presented in SAP 2009 document (BRE, 2012) to diagnose the likelihood of overheating for the existing English housing stocks. The authors increased the mean summer external temperature by 1.4°C to represent the warming climate by the 2080s, which is in accordance with the UK regional climate projections. It was estimated that 82% of English housing stocks showed at slight risk (see description in Table 2-7) and 12% at high risk under current climate while 99% and 38% at slight and high risk respectively by the 2080s. The authors suggested that overheating risk could be reduced by efficient ventilation but the ventilation strategy in practice was likely to be restricted by external environmental issues such as security and noise; besides, solar shading was found to be an effective passive intervention. Even if with passive adaptations 66% of English housing stocks would show a slight risk of overheating due to the increase of 1.4°C by the 2080s. It was also found that the post-1930 dwellings (typically with cavity wall construction) were more likely to be at a higher risk of overheating than the pre-1930 dwellings (typically with solid wall construction) while post-1983 dwellings were prone to at least a slight risk due to the high level of insulation. Overheating risk for the post-1983 flats would be very unlikely to be eliminated with any passive adaptations by the 2080s. Due to the limitations in simple SAP method which is solely based on the monthly weather data, it cannot measure the duration and severity of overheating which requires higher temporal weather time series.

d) Linear regression models and probabilistic approach

As some of the uncertainties in the estimation of future overheating risk are inherited from the climate change projections and would increase as time goes on, de Wilde and Tian (2012) recommended using a probabilistic approach to explicitly quantify the uncertainties and to make a risk-based predictions. Likewise, Patidar *et al.* (2011), Jenkins *et al.* (2011) and Gul *et al.* (2012) suggested that future overheating risk should be presented in the form of a probability distribution so that building practitioners are able to identify an acceptable probability, and provide adaptations to protect occupants from the most likely future climate projections. As mentioned in subsection 2.5.5, future summer reference years created based on the outputs from UKCP09 WG, which incorporates the probabilistic UKCP09 climate change projections (see subsection 2.5.4 and 2.5.5), have been used in dynamic thermal simulation in recent years. The high variation in the probabilistic UKCP09 climate change projections would lead to a great variation in overheating estimated. For example, the variation in mean annual external temperature would be 5.5°C by the 2050s under medium emission scenario which could result in a variation of 4.75°C in mean annual internal temperature (Kershaw *et al.*, 2011). Therefore, dynamic thermal simulations with multi-year probabilistic reference years were unavoidable in order to uncover the potential thermal performance of buildings with the likely range of future climate change projections (Kershaw *et al.*, 2011). Kershaw *et al.* (2011) found that five probabilistic reference years (i.e. the 10^{th}, 33^{rd}, 50^{th}, 66^{th} and 90^{th} percentile TRYs produced by (Eames *et al.*, 2011)) were enough to well represent the shape of cumulative distribution formed by all 3,000 example years created based on the UKCP09 WG outputs. It would be, however, more accurate to run thermal simulations with all 3,000 example years to identify the probabilistic risk from the aspect of the indoor thermal condition rather than external weather condition. The various building characteristics differ sensitivity to different weather variables so that the percentile of a future summer reference year is not equivalent to the same percentile of the risk of overheating. For instance, the 10th, 50th or 90th percentile future summer reference years could not deliver the same 10th, 50th or 90th percentile overheating risks. To perform dynamic thermal simulations with all 3,000 example years (i.e. 3,000 iterations) for a single building is, however, time-consuming and impractical for building practitioners (Eames *et al.*, 2011). Coley and Kershaw (2010) proposed an efficient way to appraise the resilience of building design against a warming climate. The authors found a linear relationship between the increase in mean (or maximum) external temperatures due to climate change and the increase in mean (or maximum) internal temperatures. The gradient could be determined by two simulations. It was termed as climate change amplification coefficient by Coley and Kershaw (2010). The weakness of this approach is that the response of the buildings to a single weather variable, i.e. mean or maximum temperature was considered rather than all the thermally related weather variables, e.g. solar radiation and wind speed. Patidar *et al.* (2011), Jenkins *et al.* (2011) and Gul *et al.* (2012) also developed a regression model based on the hourly external weather data and the hourly internal temperatures which could be initially provided by a single run of dynamic thermal simulation. Patidar *et al.* (2011) tried to use a full set of 3,000 example years to estimate overheating risks based on the regression model instead of 3,000 iterations of dynamic thermal simulations which are computationally expensive. Patidar *et al.* (2011) found that overheating risks predicted with 100 randomly selected years could well represent those with a full set of 3,000 example years. More importantly, Patidar *et al.* (2011) and Jenkins *et al.* (2011) drew the same conclusion that the regression approach was solid as the overheating risks from the simple regression model agreed remarkably well with the ones from dynamic thermal simulations. In addition, the adaptation interventions in reducing overheating risk could be tested with the regression model. Nevertheless, Patidar *et al.* (2011) failed to show whether or not the regression approach is appropriate for the large and complex non-domestic buildings. Gul *et al.* (2012) stated that the internal hourly temperatures for domestic buildings could be predicted solely based on external climate as Patidar *et al.* (2011) did while internal heat gain profiles should be considered together with the external weather for the large and complex non-domestic buildings. Regarding overheating risk assessment with probabilistic climate change projections, Coley *et al.* (2012) raised an important issue that building modellers might be uncertain about what level of climate change projection the building design should be subjected to. This would make people not confident about the structural adaptations (e.g. increasing thermal mass, installing fixed shading device and solar control glass) which are recommended to use for mitigating the adverse effect of the warming climate. Coley *et al.* (2012) found that behavioural adaptations, such as the opening window, were as effective as structural adaptations which cost money; furthermore, the errors resulted by selecting an incorrect climate change projection could be offset by behavioural adaptations. As Coley *et al.* (2012) presented overheating hours (occupied hours >28°C) with the structural adaptations predicted at the 50th percentile projection (i.e. a medium warm projection) for the 2050s were similar to overheating hours with a combination of structural and behavioural adaptations predicted at the 90th percentile projection (i.e. an extremely warm projection). This indicates that the incorrect probabilistic climate projections would not result in extra cost due to the great effectiveness of potential and free behavioural adaptations.

2.6.3. Spatial variation in overheating risk

Overheating risk substantially varies with different building characteristics as well as weather. Neither of them is uniform across a landscape so that there would be a spatial variation in overheating. Building characteristics, local shading and weather files at a fine resolution are essential in order to measure the magnitude of spatial variation. As stated in section 2.4, it is not easy to obtain measured building information and surrounding obstructions at a high spatial resolution. A few standard dwelling models for typical dwelling types or a great number of thermal models generated by augmenting dwelling archetypes with various building characteristics have been used in previous modelling based thermal comfort studies (Mavrogianni *et al.*, 2012; Oikonomou *et al.*, 2012; Taylor *et al.*, 2014; Gupta and Gregg, 2012; Gupta and Gregg, 2013) (see subsection 2.4.3). The detailed building measurement at a large scale is highly expensive and time-consuming so that it is rare to find studies using a large number of dynamic thermal models individually created based on measured building information and taking account of local shading effect.

However, weather data is available at a high spatial resolution, which has made it feasible to study the impact of natural variability in localised climate on thermal performance of buildings. For example, the UKCP09 WG is able to offer both current and future hourly weather data at 5km by 5km horizontal resolution (see subsection 2.5.4). There is no spatial coherence between neighbouring grids due to the random sampling method of the UKCP09 WG that treats each 5km by 5km grid independently (Jones *et al.*, 2010; Kilsby *et al.*, 2007). Random seeds prime the UKCP09 WG, which leads to inconsistent outputs for the same grid location. Nonetheless, the difference between outputs caused by different random seeds is far less than the difference between neighbouring grid locations, indicating that the UKCP09 WG is suitable for studying the correlation between spatial variation in climate and overheating risk (Eames *et al.*, 2012a). Eames *et al.* (2012a) investigated the spatial variation in thermal performance of a house and a school across two regions: one with uniform topography and the other with non-uniform topography. Both current and future weather files were created at 5km by 5km resolution for each region. It was found that overheating risk (i.e. hours above 28°C from May to September) was highly diverse across the latter region. This finding suggests that localised weather files are significantly important for accurate overheating risk assessment in the region with non-uniform topography. Eames *et al.* (2012a), in addition, identified that spatial variation in future climate was similar to that in current climate indicating that topography is unlikely to influence localised climate change projection.

Demanuele *et al.* (2012) also examined the impact of spatial variation in external temperatures on the internal temperature of a naturally ventilated office. The external hourly temperatures of 20 sites along the east-west transect in London are available from the London Site Specific Air Temperature (LSSAT) model. Kolokotroni *et al.* (2009) developed LSSAT which is an artificial neural network model trained by hourly air temperature measured for one year from 77 sites in London. Other weather variables, such as GIRad, RH and WS, required for building simulation were derived from the nearest weather station and remained constant across the city. A high variation in overheating hours above 28°C along the east-west transect was presented due to the spatial variation in external temperatures. Demanuele *et al.* (2012) emphasised the importance of the site-specific weather files to the assessment of overheating risk, which is in line with the previous statement from Eames *et al.* (2012a). The downside of this study is that other thermally related weather variables were assumed to be unchanged along the east-west transect as they were unavailable at a fine spatial resolution.

Both studies (Demanuele *et al.*, 2012; Eames *et al.*, 2012a) focused on the spatial variability in the localised weather but made no attempts to address the variability of the building types and local shadings which may also have a significant impact on spatial variation in overheating.

Taylor *et al.* (2015) predicted the spatial variation in excess mortality attributable to the high internal temperature at a fine resolution in London. The urban heat island (UHI) effect was modelled at 1km by 1km resolution across the city using Met Office–Reading Urban Surface Exchange Scheme (MORUSES) developed by Porson *et al.* (2010). The high-resolution UHI data combined with existing weather data, derived from a few nearby weather stations and current weather files (i.e. London DSY created by Eames *et al.* (2011)), were used to construct site-specific weather files while dwelling archetypes were used in thermal modelling to predict internal temperatures. The gap between prediction and reality could be minimised if the variability of local dwelling characteristics and shading effects are considered in thermal modelling. Taylor *et al.* (2015) found that both dwelling types and UHI effect had a significant impact on the spatial variation in internal temperatures, whereas dwelling types had a greater impact compared to UHI effect, which supported previous work (Oikonomou *et al.*, 2012). Taylor *et al.* (2016) mapped the risk of overheating in the UK based on thermal models with no concern on UHI effect. Nevertheless, it was found that overheating risk in urban areas is higher than the rural areas since a greater number of flats and terraced houses, which are more likely to overheat, located in the urban areas compared to rural areas (Taylor *et al.*, 2016). In contrast, the risk of heat-related mortality would be higher in the rural area than the urban area due to the greater elderly population in the rural area (Taylor *et al.*, 2015), which indicates that population age plays a key role in predicting the risk of heat-related mortality.

2.6.4. Summary

Regardless of assessment methods (e.g. household interview, monitoring and thermal simulation), assessment criteria (e.g. static and adaptive criteria) and climates (e.g. current and future climates), a considerable number of UK dwellings have been found to overheat. Dwelling types, property age, insulation level, occupant behaviours (including occupied hours), surrounding environmental condition, and so on have a great influence on the propensity to overheat. For instance, top floor flats are more likely to overheat compared to other dwelling types; old dwellings with solid wall and poor insulation are less likely to overheat than modern dwellings with cavity wall and good insulation; the detached houses are also less likely to overheat when external temperature is lower than internal temperatures due to its greater exposed wall area from which more internal heat can be released. As expected, the risk of overheating is on the rise due to the warming climate. Passive adaptations such as shading, solar reflective coating, thermal insulation and natural ventilation are effective in reducing the risk of overheating. External insulation and shading are more effective than the internal insulation and shading. Internal insulation should be used with caution as it has a negative impact on the radiative cooling effect of thermal mass. For some cases, the internal insulation was likely to increase the risk of overheating. Internal shading such as blinds and curtains cannot reflect all sunlight back to the outdoor and the remaining would be quickly converted to heat. Since the solar gain is preferable during the heating season, operable shading devices are recommended. Behavioural adaptation such as opening window plays an important role in mitigating increasingly high overheating risk but it may be restricted due to the issues with security, noise, air pollution, and so on. It is true that overheating risk can be significantly reduced by passive adaptations. Nonetheless, even the combination of the most effective passive adaptations would not thoroughly eliminate overheating risk estimated under a warming climate. Therefore, active adaptation, e.g. air-conditioning should be seriously taken into account while using the passive adaptations in the first place to minimise cooling energy demand. In addition, probabilistic approaches have been recommended to investigate overheating risk under a changing climate so that the uncertainties in the climate projections can be explicitly quantified. In the light of probabilistic future overheating analysis building practitioners and clients are able to make risk-based decisions to improve the resilience of buildings. There would be a high spatial variation in overheating risk across a landscape due to the variability in dwelling types, local shading and climate. Dwelling types place a greater impact on spatial variation in overheating risk compared to localised weather. However, the details of real dwellings and context are rarely available at a large scale for thermal modelling. This has become the main issue that needs to be overcome when investigating spatial variation in overheating. It is, therefore, crucial to measure local dwellings and local shadings and then create dynamic thermal models individually based on the measurement in order to take account of realistic variability in local dwellings and shadings across a region.

3. Creation of New Future Hot Summer Years

The content of this chapter is from a paper entitled ‘Future probabilistic hot summer years for overheating risk assessments’ which has been published in the journal of Building and Environment. The authors are C. Liu, T. Kershaw, M.E. Eames and D.A. Coley. Regarding this paper, the statement of authorship form and evidence of permission can be found in Appendix B and C respectively. The data access of this academic paper is shown in the results section.

This chapter presented two alternative approaches for the development of current and future weather files: one (pHSY-1) is based on Weighted Cooling Degree Hours (WCDH), the other (pHSY-2) is based on Physiologically Equivalent Temperature (PET). The pHSY-1 and pHSY-2 files were produced for fourteen locations. These were then compared with the existing probabilistic future Design Summer Year (pDSY) and the probabilistic future Test Reference Year. It was found that both pHSY-1 and pHSY-2 are more robust than the pDSY. It is suggested that pHSY-1 could be used for assessing the severity and occurrence of overheating, while pHSY-2 could be used for evaluating thermal discomfort or heat stress. The results also highlight an important limitation in using different metrics to compare overheating years. If the weather year is created by a ranking of a single environmental variable, to ensure consistent results assessment of the building should be with a similar single metric (e.g. hours >28°C or WCDH), if however the weather year is based upon several environmental variables then a composite metric (e.g. PET or Fanger’s PMV) should be used. This has important implications for the suitability of weather files for thermal comfort analysis.

3.1. Introduction

Two central functions of buildings are to provide shelter from the external environment and to ensure thermal comfort for the occupants. Given the lifetime of buildings, shelter and comfort need to be ensured over a considerable time frame. Under the RCP8.5 greenhouse gas emissions scenario, projections of global mean surface temperatures show an increase of between 2.6°C and 4.8°C by the end of this century, relative to a 1986 to 2005 baseline (IPCC, 2013). The estimation of temperature increase is highly dependent upon the emission scenarios. According to the 2015 Paris Climate Conference, the increase of global temperature will be limited to 1.5°C (relative to pre-industrial level) by 2020s due to the international efforts in reducing greenhouse gas emission (UNFCCC, 2015). Research predicts a significant increase in overheating risk under a changing climate with different emission scenarios (Demanuele *et al.*, 2012; Gupta and Gregg, 2012; Jentsch *et al.*, 2008; McLeod *et al.*, 2013; Patidar *et al.*, 2011; Taylor *et al.*, 2014). People with cardiovascular and heart-disease are more vulnerable (Vandentorren *et al.*, 2006; Portier CJ *et al.*, 2010) and would be under higher risk of heat-related illness due to the global warming. Therefore acceptable internal conditions within buildings need to be demonstrated under a climate that will change considerably, and industry and academia supported in doing so with the provision of suitable weather time series.

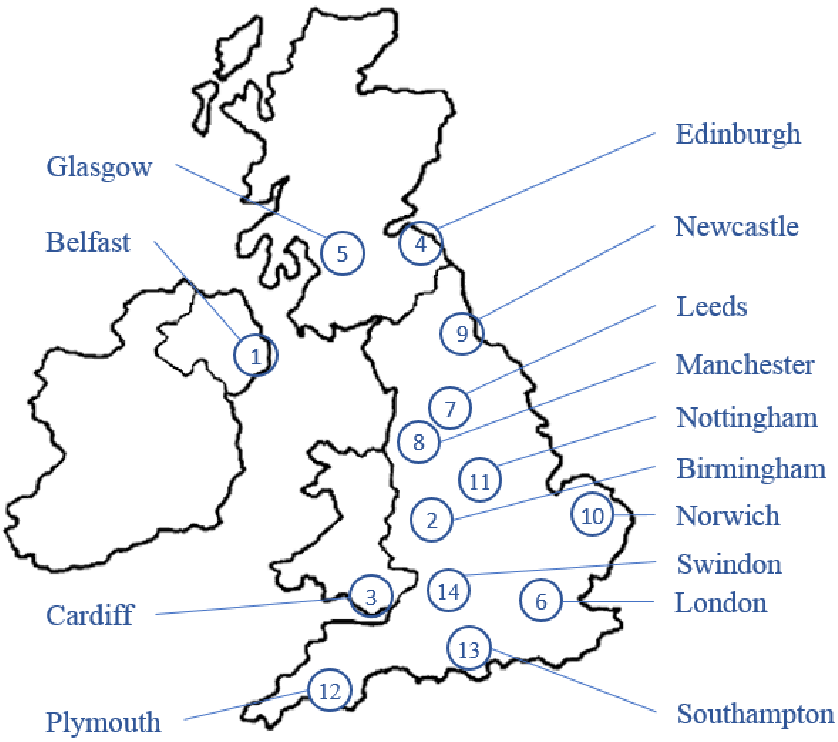


Figure 3-1. Map of the UK showing the fourteen sites used by CIBSE for the DSY and TRY.

The CIBSE provides Design Summer Years (DSY) for assessing overheating risk for fourteen sites across the UK (see Figure 3-1). The CIBSE DSY is a continuous year picked from around 21 years (typically 1983-2004) of observed weather data based on a simple selection method (Levermore and Parkinson, 2006). The 21 years of weather data are ranked in ascending order according to the mean summer (April – September) dry bulb temperature. The DSY is the year ranked at the middle of upper quartile (typically the third warmest). This methodology however, has several issues. For instance, among the 21 years, years with significant amounts of missing data were discarded so that the number of complete years available for each site varied from 6 (Southampton and Swindon) to 21 (Edinburgh and Glasgow). Thus DSYs exist for sites with a small number of complete years which hence might not be particularly warm compared to the long-term mean (Jentsch *et al.*, 2013). CIBSE also provides Test Reference Years (TRY), which are used for predicting the energy consumption of buildings. Unlike the DSY, the TRY is designed to be a typical year. The CIBSE TRY is a composite year which consists of the 12 most representative months, chosen from the 21 years of historical weather data. The most representative January, February and so on are individually selected using Finkelstein-Schafer (FS) statistics based upon air temperature, solar radiation and wind speed (Levermore and Parkinson, 2006). Unfortunately it is known that, when applied to a building, the CIBSE TRY can predict greater overheating risk than the CIBSE DSY for some sites e.g. Norwich and Newcastle (Jentsch *et al.*, 2013), this is the reverse of what might be expected. It was found that updating the baseline data to a more recent period with better data could not solve this issue (Jentsch *et al.*, 2015). For instance, the updated DSY remained the same as the original DSY for Norwich and Newcastle.

There have been alternatives to the CIBSE DSY approach suggested for overheating studies. Jentsch *et al.* (2015) proposed a near-extreme summer reference year (SRY) which is a composite year where the current TRY selection process was adjusted to a candidate year with many degree hours >18°C and another candidate year with high direct solar radiation to generate one SRY that includes extreme temperatures and high solar radiation. The resultant SRY (Jentsch *et al.*, 2015) consistently indicated more severe overheating risk than the TRY at the fourteen sites when used in a simulation of a non-realistic building (CIBSE, 2006b). Instead of a single DSY, Eames (2016) presented three probabilistic DSYs for one location to investigate a range of potential overheating risks. These new DSYs were selected from updated baseline weather data (1983-2013) based on the analysis of actual warmest events and their return periods. The three probabilistic DSYs were defined as a moderate warm event year, an intense extreme year and a long extreme year respectively. A generalised extreme value (Coles, 2013) was used for estimating return periods of the hot event year. Weighted cooling degree hours (WCDH), combined with two alternative overheating metrics were used to determine the warmest events. The alternative overheating metrics are the static weighted cooling degree hours (SWCDH) and the threshold weighted cooling degree hours (TWCDH). SWCDH took account of regional threshold temperatures related to excess summer mortality, while TWCDH combined the adaptive comfort temperature with the regional threshold temperature. Though there have been different approaches to the current summer reference years to be used for dynamic thermal simulations in other countries (David Ferrari and Lee, 2008; Frank, 2005), basically mean dry bulb temperature was used to measure the warmth of summer.

In addition to the CIBSE TRY/DSYs which are intended to be representative of the current climate, future TRY/DSYs have been created in the UK. CIBSE incorporated the UK Climate Impacts Programme (UKCIP02) climate change scenarios via a mathematical transformation (termed morphing) into the current TRYs and DSYs to create the future CISBE TRYs and DSYs. Since the future CIBSE TRY/DSYs are based upon a mathematical transformation of the historic files, the issues mentioned above still exist in the future CIBSE DSYs. Thus the improvement of future DSYs has become an important issue.

The morphing approach (Belcher *et al.*, 2005) uses averaged historical observations of weather as a baseline and climate change projections from a climate model. The morphing algorithms apply the monthly climate change projections to the baseline historical data depending on the weather variable to create the future weather data. For example, the Climate Change Weather File Generator (Jentsch, 2012)developed by the University of Southampton uses this method to combine CIBSE TRYs and DSYs with UKCIP02 climate change projections to create future weather files for the UK. The main limitation with this method is that it is reliant upon observed weather data spanning many years (in order to form the baseline TRYs and DSYs), which is unavailable for many locations. The other method is based on the UKCP09 weather generator (Jones *et al.*, 2010), which can produce daily and hourly synthetic weather data for both a control period (1961-1990) and future time periods (from 2020s to 2080s) at a 5 km by 5 km grid resolution. The UKCP09 weather generator has allowed researchers to create time series of current and future weather without having to rely upon historical observations, and this has led to several novel approaches (Smith and Hanby, 2012; Eames *et al.*, 2011; Watkins *et al.*, 2012) for the creation of future DSYs.

The DSY was intended to represent a warm but non-extreme year, which could be used to assess summertime overheating. However, it is known that the temperature inside a building is dependent on more than just the external temperature, including wind speed, solar radiation and relative humidity. It has been shown that although the DSY is ranked the 3rd warmest externally amongst the 21 or so years of weather observations, its ranking falls when considering internal temperatures and thermal discomfort (Kershaw *et al.*, 2010). The method for the creation of the DSY selects a warm year, but this may be as a result of a warmer than typical spring, rather than a hotter than normal summer, or the existence of any heat wave. (When considering morbidity or mortality from thermal stress it is uncharacteristically high temperatures sustained over several days, humidity and wind speed that are important.) Kershaw *et al.* (2010) compared TRYs and DSYs to the baseline datasets used to create them; they found that years such as 2003, which resulted in so-many deaths across the UK and Europe, are not necessarily ranked highly by the DSY selection procedure. For instance 2003 is ranked 14th out of 19 in terms of mean summertime external temperature in Plymouth. Indeed, the DSY selection process consistently underestimates the potential amount and severity of overheating and thermal discomfort within the buildings.

There is therefore a need to create new reference years that can provide additional information about overheating risk in buildings and the risk to human health. In this paper we describe the creation of two new reference years termed 'hot summer years': one based upon weighted cooling degree hours, which will highlight years with high temperatures and another based upon the physiologically equivalent temperature, which is dependent upon both air and radiant temperatures, humidity and wind speed. It is hoped that these new reference years will enable practitioners to examine the risk of overheating and thermal discomfort within their building designs in a more holistic manner.

3.2. Methodology

In order to distinguish the new summer years from the existing probabilistic future DSYs (pDSY), the new summer years are referred to as probabilistic Hot Summer Years (pHSYs). In the following the two methods are presented and compared with the methods used for the future probabilistic TRY (pTRY) and pDSY. The probabilistic Hot Summer Year No.1 (pHSY-1) is based upon assessment of weighted cooling degree hours (WCDH), the probabilistic Hot Summer Year No.2 (pHSY-2) is based upon assessment of the physiologically equivalent temperature (PET). All four weather years were created using the same future weather data for 2050s under the high emission scenario (SRES A1FI) and produced by the UKCP09 weather generator, however the method is a general one, and other emission scenarios or time periods could be used. Three percentiles (10th, 50th, and 90th) were created for pDSY, pHSY-1, pHSY-2 and pTRY type files for the same fourteen UK sites (see Figure 3-1) that current CIBSE DSYs and CIBSE TRYs are normally offered. Once these files were created, the risk of overheating and thermal discomfort was investigated using a reference conceptual building outlined in CIBSE TM 49 (CIBSE, 2014). The reference conceptual building is a free running building in which the internal operative temperature is assumed to be the same as the external dry bulb temperature. According to the CIBSE TM 49 (CIBSE, 2014), this reference model is appropriate for representing naturally ventilated buildings such as UK domestic houses so that it was introduced to develop a new summer reference year for overheating risk assessment in the UK.

3.2.1. Two approaches for future probabilistic Hot Summer Years

The pHSY-1 is based on WCDH (Nicol *et al.*, 2009; CIBSE, 2014) during the summer (June, July and August), while the pHSY-2 is based on the hours of PET >23 °C, which is defined as warm and slight heat stress, this value is equivalent to a PMV of >0.5 above which the space is considered as not providing thermal comfort (Matzarakis and Mayer, 1996).

The WCDH is given by:

$$T_{comf} = 0.33T_{rm} + 18.8 \tag{3-1}$$

and

$$WCDH = \sum_{all\ hours}\left(T_{op} - T_{comf}\right)^2, T_{op} - T_{comf} > 0, \tag{3-2}$$

where T_{comf} is the comfort temperature (°C) predicted from the adaptive comfort model given in BS EN15251 (BSI, 2007), T_{rm} is the running mean outdoor temperature (°C), and T_{op} is the indoor operative temperature (°C). The use of a quadratic difference between T_{op} and T_{comf} increases the emphasis on the discomfort temperature. Smith and Hanby (2012) presented different methods for creating future design summer years and used WCDH to measure the warmth of their years. It was found that the differences between the methods were enlarged due to the higher impact on the larger differences between T_{op} and T_{comf}. CIBSE TM49 (CIBSE, 2014) also suggested the use of WCDH to measure the warmth of 32 years of observed weather data (1975 to 2006) and selected the years with the hottest summer and a moderately warm summer i.e. 1976 and 1989 for London. Year 2003 was also selected as it showed a high WCDH during a short hot spell, namely the August 2003 heatwave.

As thermal comfort is affected by not only temperature but also other thermally related weather variables, PET was used for creating pHSY-2. PET was developed by Mayer and Höppe (1987) and has been recommended in German building guidelines (VDI, 1998) as one of the main thermal indices. It considers all the thermally related weather variables such as air temperature, solar radiation, relative humidity and wind speed. Based on the Munich Energy-balance Model for Individuals (MEMI) (Höppe, 1984; Höppe, 1993), outdoor air temperature is converted into an equivalent temperature in a typical standardised indoor environment where it is assumed that the air temperature is equivalent to the mean radiant temperature, air speed is equal to 0.1m/s and water vapour pressure is 12 hPa. Real comfort values for skin temperature and sweat rate are dependent on activity as well as climate, however, in line with the empirical data, the expected comfort values were used in Fanger's PMV calculation. Unlike Fanger's PMV approach, in which these comfort values were only dependent on activity, MEMI quantifies real skin temperature and sweat rate for activity and a given climate (Höppe, 1993).

For the work reported here, the bioclimatic model RayMan Pro produced by the Meteorological Institute of the University of Freiburg was used to calculate PET, as it contains the MEMI model and has been used in urban climate studies (Matzarakis *et al.*, 2007; Lin *et al.*, 2010; Lin and Matzarakis, 2008). Figure 3-2 shows the procedure of generating pHSY-1 and pHSY-2. One hundred sets of 30-year complete weather files are constructed by combining outputs from the UKCP09 weather generator with missing weather variables such as wind speed and direction, generated as described above. Each set represents a single sampling of the UKCP09 climate change probability density function for the site. Hence the 100 sets cover predictions of little climate change to aggressive change. For each set of 30 years, the year with the highest WCDH is chosen as one HSY-1. In total, 100 HSY-1 are derived from the 100 sets. These 100 HSY-1 are distinct, since they inherit 100 probabilistic climate projections from UKCP09. These 100 HSY-1 are then sorted in ascending order of WCDH to produce pHSY-1. The pHSY-2 are created in the same way but using hours of PET>23°C, rather than WCDH.

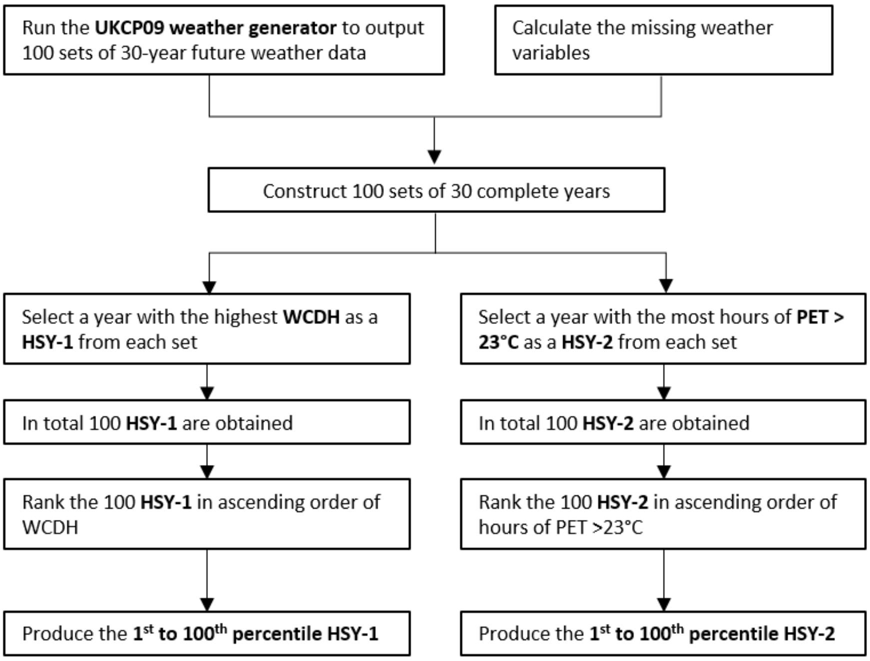


Figure 3-2. Procedure for creating pHSY-1 and pHSY-2.

In addition, future pTRYs and pDSYs were produced in order to compare the pHSY-1 and pHSY-2 with them. For the purpose of maintaining the original methods used for the creation of the CIBSE TRY and DSY, the method suggested by Eames *et al.* (2011) was used for creating the future pTRYs, while the method for creating future pDSYs was that suggested by (Smith and Hanby, 2012). That is, the FS function used in CIBSE TRY and the simple selection method used in the CIBSE DSY (Levermore and Parkinson, 2006). These were applied to the 100 sets of 30-year time series of weather data to produce 100 TRYs and 100 DSYs respectively. From these 100 candidate years, pTRYs and pDSYs were produced based on sorting the years into ascending order of mean summer temperature. (pTRY is a composite year while pDSY is a continuous year, as in CIBSE TRY and DSY.) The comparison between the methods used for the pHSY-1, pHSY-2, pDSY and pTRY are described in Table 3-1. The missing weather variables were calculated based on the methodologies presented in Table 3-2.

Table 3-1. Comparison of the methods for creating pTRY, pDSY, pHSY-1 and pHSY-2.

	Typical year (Composite)	Summer years (Continuous)		
	pTRY	pDSY	pHSY-1	pHSY-2
Methods	**CIBSE TRY method** Finkelstein-Schafer statistics functions	**CIBSE DSY method** The third hottest mean summer temperature (April to September)	**WCDH** during summer (June to August)	**Hours of PET > 23°C** during summer (June to August)
Ranking method	Ascending order of mean summer temperature	Ascending order of mean summer temperature	Ascending order of WCDH	Ascending order of the hours of PET >23°C
Usages	Energy performance assessment	Potential overheating risk and thermal discomfort assessment in free running buildings (i.e. non-air conditioned buildings)		

Table 3-2 Methodologies used for missing weather parameters generation

Missing weather parameters required in EPW		**Unit**	**Methodologies and references**	**Correlative weather variables from the UKCP09 WG**
Temperature	Ground Temperature	°C	Kusuda (1965),Lawrie (2003)	Maximum and minimum daily air temperature
	Dew point temperature (dpt)	°C	ASHRAE (2005)	Hourly vapour pressure
Solar radiation	Extra-terrestrial horizontal radiation (I_{exhor}) Extra-terrestrial direct normal radiation(I_{exnor})	Wh/m^2	CIBSE Guide J	
	Horizontal infrared radiation from the sky (L_{sky})	Wh/m^2	CIBSE Guide J	Hourly sunshine fraction, mean air temperature and vapour pressure
	Global horizontal radiation (G_h) Direct normal radiation (B_{nh}) Diffuse horizontal radiation (D_h)	Wh/m^2	Kasten and Czeplak (1979), Watkins *et al.* (2011), CIBSE Guide J	Hourly sunshine fraction
daylight	Global horizontal illuminance (E_{vg}) Direct normal illuminance (E_{vb}) Diffuse horizontal illuminance (E_{vd}) Zenith luminance (L_{vz})	Lux Lux Lux Cd/m^2	Perez (1990), Kasten (1965)	Sunshine fraction and hourly precipitation
Wind	Wind direction Wind speed	degree m/s	Eames *et al.* (2010), Ekström *et al.* (2007)	Daily solar radiation, vapour pressure and PET*[a)]
Atmospheric pressure		Pa	Eames *et al.* (2010)	
Sky cover	Total sky cover (cc_t) Opaque sky cover (cc_{op})	deca	The same method used in the EPW	Hourly sunshine fraction

Note: a) PET* stands for Potential EvapoTranspiration

3.2.2. Assessment methods

Typical years such as the pTRY are used for assessing the energy performance of buildings while the concept of summer years such as the pDSY, pHSY-1 and pHSY-2 are used for assessing risk of overheating and thermal discomfort. The method used for the original CIBSE DSY is not robust, in that, it can indicate less overheating than the CIBSE TRY for some UK sites such as Newcastle, Norwich and Nottingham (Jentsch *et al.*, 2013). Kershaw *et al.* (2010) also found that the DSY is likely to underestimate the overheating risk due to its simple selection method. The robustness of the pHSY-1 and pHSY-2 were examined by comparison with the pTRY and pDSY for the fourteen UK sites. Four assessment metrics were used as follows:

(1) WCDH (same as the warmth measurement used for pHSY-1 creation)
(2) Hours of temperature >28°C (a common measure of overheating in building regulations)
(3) Hours of PET >23° C (same as the warmth measurement used for pHSY-2 creation)
(4) Hours of PMV >0.5 (a common measure of thermal comfort in building regulations)

Assessment metric (2) refers to CIBSE Guide A (CIBSE, 2006a) while (4) refers to ANSI/ASHRAE Standard 55-2013 (ASHRAE, 2013).

3.3. Results and discussion

In the following the pTRY and three probabilistic summer years (pDSY, pHSY-1 and pHSY-2) are compared in terms of overheating and thermal discomfort in a reference conceptual building. The pTRY, pDSY, pHSY-1 and pHSY-2 were compared for all fourteen sites to find out whether pHSY-1 gave greater overheating and if pHSY-2 showed more thermal discomfort hours than the pTRY at all sites (see subsection 3.3.1). In addition, low to high percentiles (e.g. 10th, 50th and 90th) of HSY-1 and HSY-2 were investigated to find out whether the overheating risk or thermal discomfort became more severe when a higher percentile was chosen (see subsection 3.3.2). If so, building practitioners would be able to choose the percentile which best represents the client's view of climate change, and the risk to occupants. For example, when designing a care home it might be best to design for a more aggressive (higher percentile) prediction of climate change than when designing a school. This is because the school can be closed and pupils not required to attend; whereas this is not possible with a care home. As stated before, each run of the UKCP09 weather generator produces 3,000 synthetic future weather files to be used in pHSY-1 and pHSY-2 creation. However, each run of UKCP09 weather generator will produce different datasets due to the random sampling method employed by the UKCP09 weather generator. Therefore, different users will be offered different datasets unless the same seed number for running the UKCP09 weather generator is used. As a check of whether this might change the amount of overheating, the impact on pHSY-1 and pHSY-2 of using different seeds is presented in subsection 3.3.3. The recommendation to the building practitioners on selecting probabilistic weather files is stated in section 3.4.

3.3.1. Investigation of the robustness of probabilistic Hot Summer Years

Figure 3-4 shows the overheating risk in the reference conceptual building caused by the 90th percentile TRY, DSY, HSY-1 and HSY-2 using assessment metrics (1) and (2), while thermal discomfort based on assessment metrics (3) and (4) is presented in Figure 3-5.

Figure 3-4 shows that WCDH calculated from the 90th percentile HSY-1 is constantly higher than that from the 90th percentile TRY in all of the fourteen sites, though the difference varies between the sites. As shown in Table 3-3, the absolute difference ranges from 924 (in Edinburgh) to 6457 (in Southampton) and the relative difference from 41% (in Nottingham) to 345% (in Belfast). On average, over the 14 sites the difference is 2707 or 186%. The 90th percentile DSY and 90th percentile HSY-2 show less overheating risk than the 90th percentile TRY for 8 of 14 sites and 9 of 14 sites respectively. The number of hours >28°C caused by the 90th percentile HSY-1 is also greater than the 90th percentile TRY in all the UK sites except Nottingham. The absolute and relative difference ranges from -43 (in Nottingham) to 208 (in Southampton) and from -22% (in Nottingham) to 544% (in Newcastle) respectively. In Nottingham however, the 90th percentile HSY-1 shows fewer hours >28°C than that of the 90th percentile TRY, but shows an increased number of hours at higher temperature (>30°C) as shown in Figure 3-3. The 90th percentile DSY and the 90th percentile HSY-2 show less overheating risk than the 90th percentile TRY for 6 of 14 sites and 9 of 14 sites respectively. The pHSY-1 was chosen based upon WCDH, which put greater emphasis on the difference between air temperature and the adaptive comfort temperature. Thus, it is likely to include more hours of high summer temperatures than the pTRY and pDSY. The pHSY-1 can be considered more robust than the pDSY when using assessment metrics (1) and (2). The CIBSE DSY selection method misses some hotter years as it is defined as the third hottest weather year. The pHSY-2 was chosen based upon PET, which considers the combined effects of all the thermally related weather variables rather than just temperature. Therefore, the 90th percentile HSY-2 may show reduced overheating risk than the 90th percentile TRY for some sites when using the assessment metrics (1) and (2), which are based solely on air temperature.

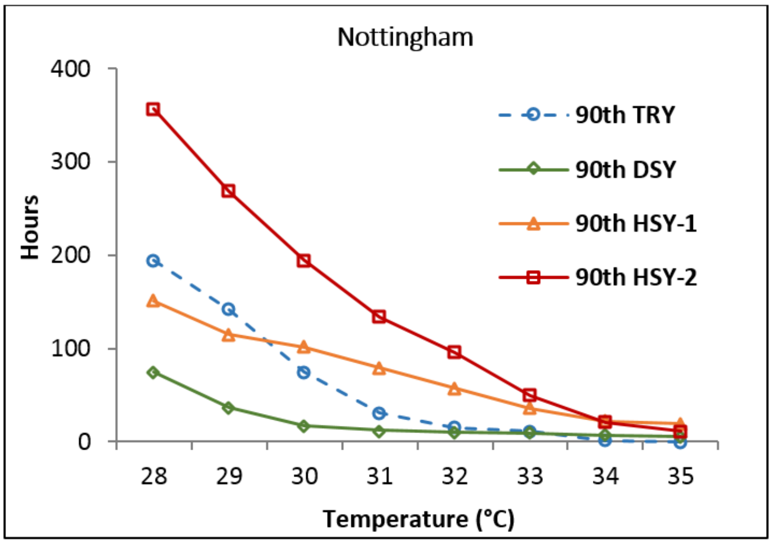


Figure 3-3. Hours of temperature above high temperatures caused by the 90th percentile TRY, DSY, HSY-1 and HSY-2 in Nottingham.

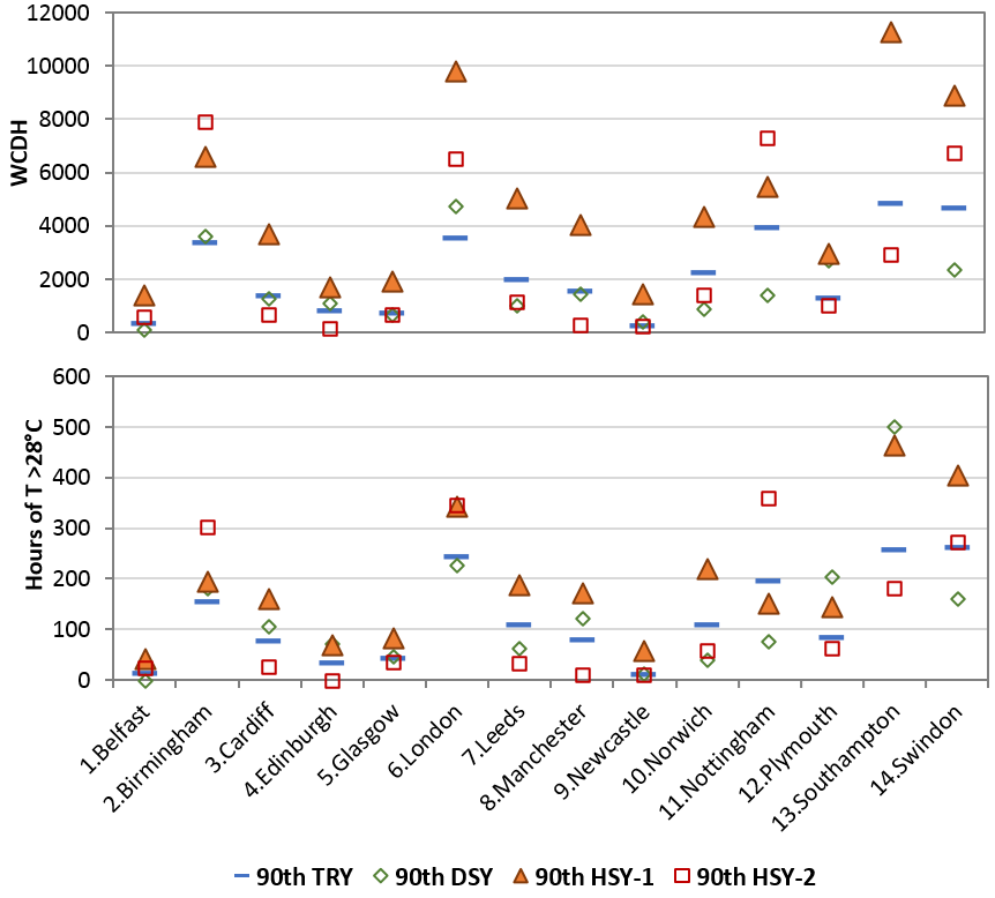


Figure 3-4. Overheating risk assessment in the reference conceptual building based on the WCDH (top) and hours of temperature >28 °C (bottom) for the fourteen UK sites. Results shown are the 90th percentile TRY, DSY, HSY-1 and HSY-2.

We can see from Figure 3-5 that the 90th percentile HSY-2 shows the greatest number of hours of PET >23°C for the fourteen UK sites. Meanwhile, the hours of PMV >0.5 are always greater for the 90th percentile HSY-2 than the 90th percentile TRY. PET and PMV are both thermal indices that estimate the level of human thermal comfort and it has been shown that there is a linear relationship between them (Augspach, 2014). The HSY-2 was chosen based upon PET >23°C, which is equivalent to a PMV >0.5, the level above which people might feel discomfort and suffer slight heat stress (Matzarakis and Mayer, 1996). Hence, using assessment metrics (3) and (4) should show similar results for HSY-2 for the fourteen sites. Mean values are 522 (σ=111) and 531 (σ=135) for hours of PET >23°C and PMV >0.5 respectively across the fourteen sites. Table 3-4 shows hours of PET >23°C and PMV >0.5 produced by the 90th percentile HSY-2 range from 76 (in Belfast) to 374 (in Plymouth) and from 42 (in Leeds) to 258 (in Plymouth) respectively. In contrast, the 90th percentile HSY-1 and DSY show fewer discomfort hours than the 90th percentile

TRY for ~50% of the UK sites, for assessment metrics (3) and (4). The methods used for pHSY-1 and pDSY ignore other thermally related weather variables that affect PET and PMV. For example, high air temperature with high wind speed and low relative humidity ratio might give a lower value of PET and PMV.

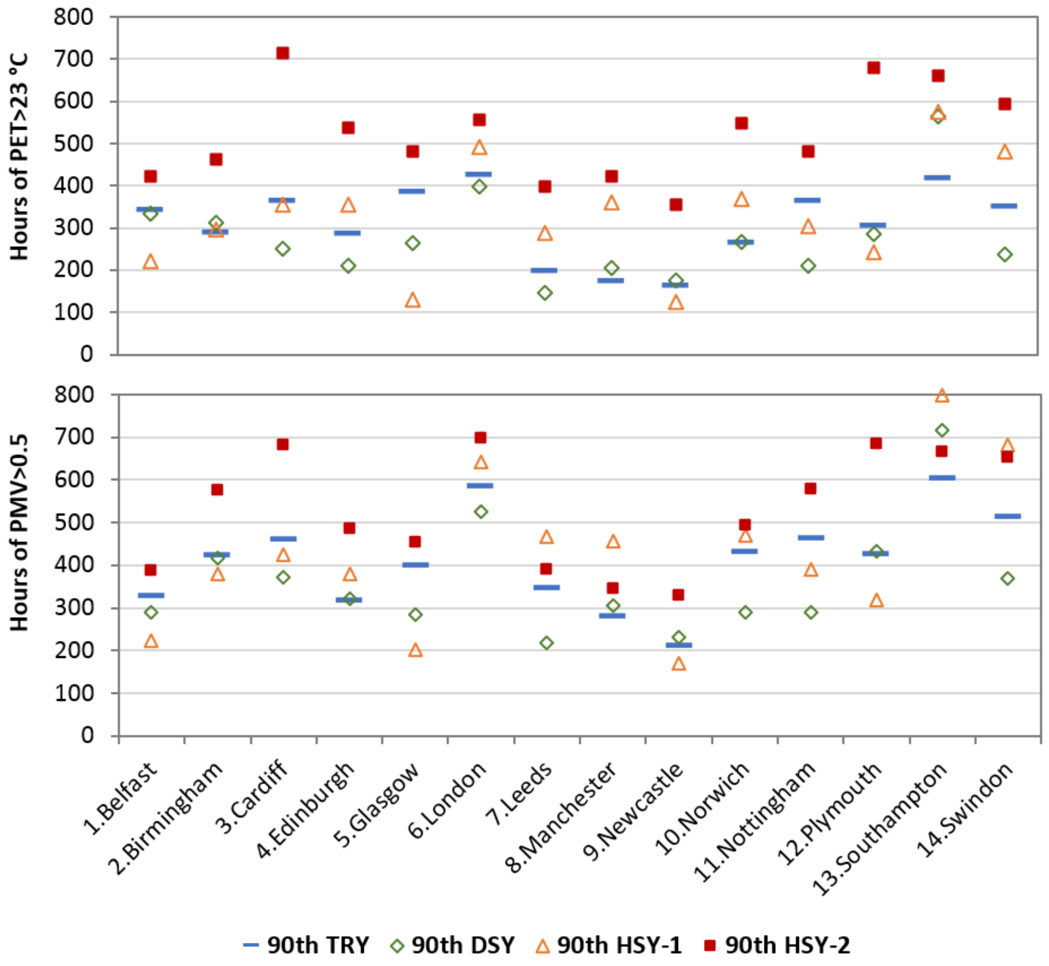


Figure 3-5. Overheating assessment of the reference conceptual building based on the hours of PET >23°C (top) and hours of PMV >0.5 (bottom) for the fourteen sites. Results are for the 90th percentile TRY, DSY, HSY-1 and HSY-2.

Table 3-3. Comparison between the 90th percentile TRY and the 90th percentile summer years i.e. DSY, HSY-1 and HSY-2 for the fourteen sites. Δ is the absolute difference and % is the relative difference between the 90th percentile TRY and 90th percentile summer years. The negative values in bold are where WCDHs and hours >28°C produced by the 90th percentile summer years are less than the 90th percentile TRY. N is the number of occurrences.

UK sites	**WCDH**				**Hours >28°C**			
	90th TRY	90th DSY Δ (%)	90th HSY-1 Δ (%)	90th HSY-2 Δ (%)	90th TRY	90th DSY Δ (%)	90th HSY-1 Δ (%)	90th HSY-2 Δ (%)
1.Belfast	311	**-238(-77)**	1075(345)	252(81)	12	**-12(-100)**	30(250)	11(92)
2.Birmingham	3312	270(8)	3250(98)	4588(139)	154	25(16)	39(25)	149(97)
3.Cardiff	1336	**-50(-4)**	2359(177)	**-699(-52)**	75	28(37)	86(115)	**-49(-65)**
4.Edinburgh	790	266(34)	924(117)	**-659(-83)**	31	40(129)	37(119)	**-31(-100)**
5.Glasgow	721	**-57(-8)**	1166(162)	**-97(-13)**	40	6(15)	41(103)	**-6(-15)**
6.London	3491	1232(35)	6272(180)	3011(86)	244	**-17(-7)**	98(40)	101(41)
7.Leeds	1953	**-958(-49)**	3069(157)	**-837(-43)**	107	**-46(-43)**	79(74)	**-76(-71)**
8.Manchester	1547	**-113(-7)**	2469(160)	**-1281(-83)**	77	43(56)	93(121)	**-69(-90)**
9.Newcastle	181	197(109)	1293(715)	**-3(-2)**	9	2(22)	49(544)	**-1(-11)**
10.Norwich	2222	**-1343(-60)**	2105(95)	**-809(-36)**	107	**-70(-65)**	111(104)	**-48(-45)**
11.Nottingham	3892	**-2522(-65)**	1588(41)	3351(86)	194	**-119(-61)**	**-43(-22)**	163(84)
12.Plymouth	1282	1429(111)	1667(130)	**-275(-21)**	82	122(149)	62(76)	**-21(-26)**
13.Southampton	4824	7290(151)	6457(134)	**-1908(-40)**	256	244(95)	208(81)	**-76(-30)**
14.Swindon	4665	**-2347(-50)**	4203(90)	2025(43)	260	**-101(-39)**	145(56)	14(5)
N/14	---	8/14	0/14	9/14	---	6/14	1/14	9/14

Table 3-4. Comparison between the 90th percentile TRY and the 90th percentile summer years i.e. DSY, HSY-1 and HSY-2 for the fourteen sites. Δ is the absolute difference and % is the relative difference between the 90th percentile TRY and the 90th percentile summer years. The negative values in bold are where hours of PET >23°C and PMV >0.5 produced by the 90th percentile summer years are less than the 90th percentile TRY. N is the number of occurrences.

UK sites	Hours of PET above 23°C				Hours of PMV above 0.5			
	90th TRY	90th DSY Δ (%)	90th HSY-1 Δ (%)	90th HSY-2 Δ (%)	90th TRY	90th DSY Δ (%)	90th HSY-1 Δ (%)	90th HSY-2 Δ (%)
1.Belfast	345	**-11(-3)**	**-125(-36)**	76(22)	12	**-39(-12)**	**-106(-32)**	60(18)
2.Birmingham	288	27(9)	9(3)	174(60)	154	**-5(-1)**	**-42(-10)**	153(36)
3.Cardiff	362	**-109(-30)**	**-7(-2)**	352(97)	75	**-90(-20)**	**-36(-8)**	222(48)
4.Edinburgh	286	**-75(-26)**	68(24)	252(88)	31	4(1)	62(20)	169(53)
5.Glasgow	386	**-122(-32)**	**-257(-67)**	95(25)	40	**-115(-29)**	**-197(-49)**	56(14)
6.London	425	**-27(-6)**	69(16)	131(31)	244	**-61(-10)**	58(10)	112(19)
7.Leeds	195	**-46(-24)**	93(48)	203(104)	107	**-131(-38)**	119(34)	42(12)
8.Manchester	172	35(20)	187(109)	250(145)	77	27(10)	177(63)	65(23)
9.Newcastle	165	12(7)	**-38(-23)**	189(115)	9	19(9)	**-42(-20)**	117(55)
10.Norwich	264	2(1)	105(40)	282(107)	107	**-143(-33)**	38(9)	63(15)
11.Nottingham	364	**-153(-42)**	**-59(-16)**	117(32)	194	**-174(-38)**	**-72(-16)**	117(25)
12.Plymouth	306	**-22(-7)**	**-65(-21)**	374(122)	82	7(2)	**-108(-25)**	258(60)
13.Southampton	416	146(35)	161(39)	245(59)	256	113(19)	194(32)	60(10)
14.Swindon	352	**-113(-32)**	127(36)	240(68)	260	**-145(-28)**	170(33)	141(27)
N/14	---	9/14	6/14	0/14	---	9/14	7/14	0/14

3.3.2. Relative performance of low to high percentile Hot Summer Years

It would be ideal to be able to use probabilistic future summer years to examine future overheating risk for a given location and design to allow risk-based decision-making. Three cumulative distribution function probability levels, i.e. 10th, 50th and 90th percentiles were investigated for the pHSY-1 and pHSY-2 based on the four assessment metrics to see whether the overheating risk or the thermal discomfort is more severe when the higher percentile is selected, i.e. that they follow a logical order.

Figure 3-6 presents overheating risk caused by 10th, 50th and 90th percentile HSY-1 based on assessment metrics (1) and (2) respectively. For all fourteen sites, the 10th percentile shows the least overheating and the 90th percentile the most overheating, suggesting that WCDH increases with the increase of percentile, as one would hope. The 50th percentile lies between the 10th and 90th percentiles and provides information about the shape of the distribution. Similarly, hours >28°C in high percentile HSY-1 are greater than in low percentile HSY-1. According to the comparison, there is a close linear relationship (R^2 = 0.92) between WCDH and hours >28°C caused by pHSY-1. Figure 3-7 presents the results from 10th, 50th and 90th percentile HSY-2 based on assessment metrics (1) and (2). The 90th percentile HSY-2 shows less overheating risk than 50th percentile HSY-2 in Cardiff, Manchester and Plymouth. In addition, the 10th percentile HSY-2 shows higher overheating risk than 50th percentile HSY-2 in London, Nottingham and Southampton. Hence, pHSY-2 is not suitable for risk-based decision making since overheating risk does not increase with the increasing percentile when using assessment metric (1) and (2).

Figure 3-8 illustrates discomfort hours caused by 10th, 50th and 90th percentile HSY-1 based on assessment metric (3) and (4) respectively. It cannot ensure that hours of PET >23°C and PMV >0.5 from pHSY-1 increase with increasing percentile. For instance, 50th percentile HSY-1 shows the lowest number of hours of PET >23°C in 5 of 14 sites. Meanwhile, 10th percentile HSY-1 shows more hours of PET >23°C than 50th percentile HSY-1 in 7 of 14 sites and, furthermore, most hours in two sites i.e. Birmingham and Plymouth. Similarly, the number of hours of PMV >0.5 caused by pHSY-1 is not higher with increasing percentile in 4 sites i.e. Belfast, Cardiff, Leeds and Plymouth. Figure 3-9 presents discomfort hours caused by 10th, 50th and 90th percentile HSY-2 based on assessment metrics (3) and (4) respectively. As expected, hours of PET >23°C, are greater in the high percentile than in the low percentile HSY-2 as they were ranked based on the ascending order of hours of PET >23°C. Due to the close relationship between PET and PMV pHSY-2 also shows more hours of PMV >0.5 with the increasing percentile. There is also a close linear relationship (R^2 = 0.88) between the hours of PET >23°C and PMV >0.5 over the fourteen UK sites.

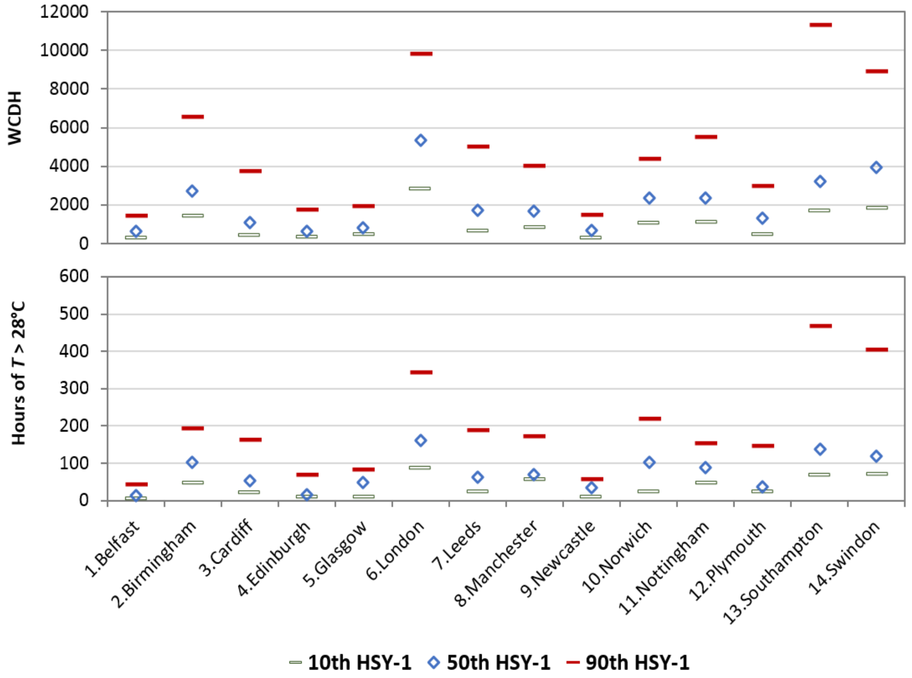


Figure 3-6. Summer overheating hours from the 10th, 50th, and 90th percentile HSY-1. Top is Weighted Cooling Degree Hours; bottom is hours of external temperature >28°C.

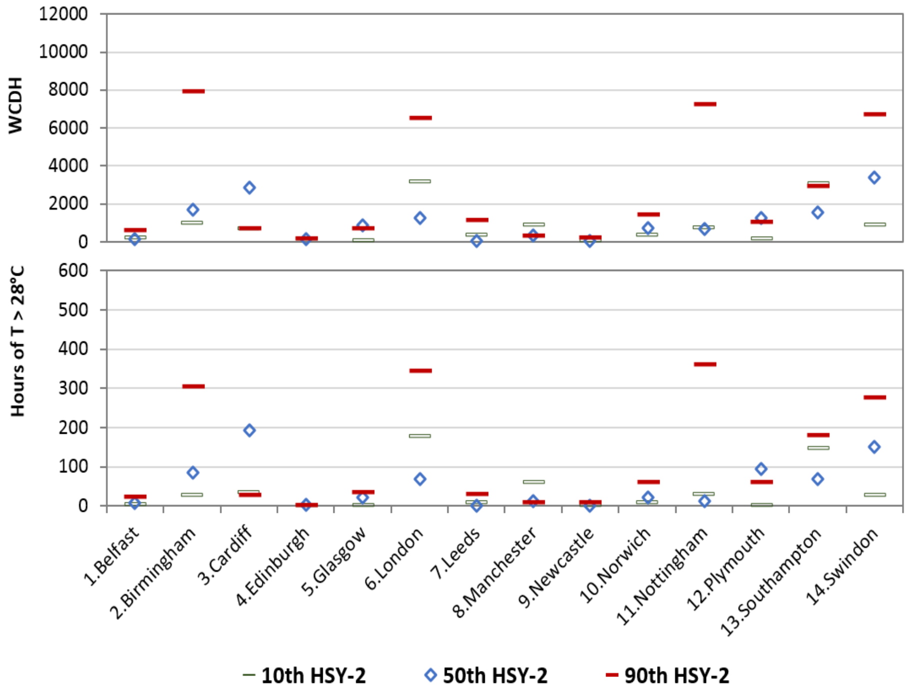


Figure 3-7. Summer overheating hours from the 10th, 50th, and 90th percentile HSY-2. Top is Weighted Cooling Degree Hours; bottom is hours of external temperature >28°C.

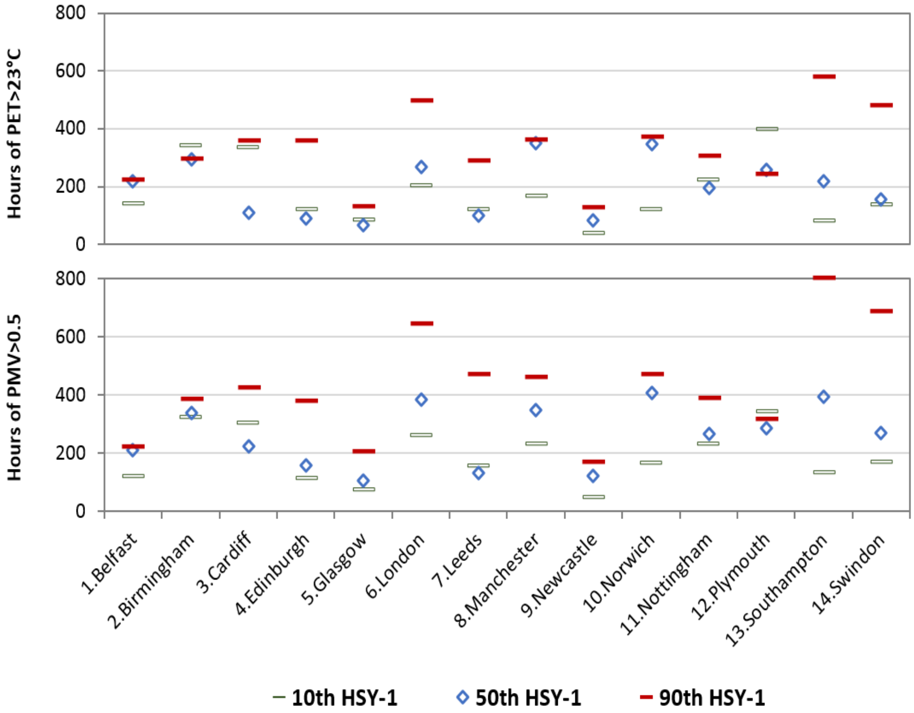


Figure 3-8. Summer thermal discomfort hours from the 10th, 50th, and 90th percentile HSY-1 based on two thermal indices i.e. PET and PMV. Top is hours of PET >23°C; bottom is hours of PMV >0.5.

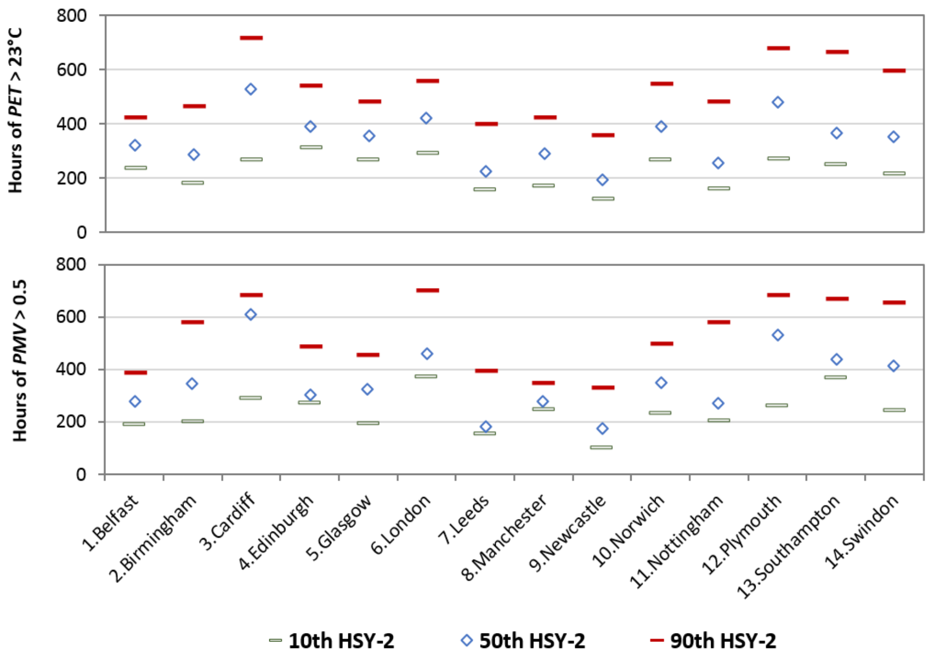


Figure 3-9. Summer thermal discomfort hours from the 10th, 50th, and 90th percentile HSY-2 based on two thermal indices i.e. PET and PMV. Top is hours of PET >23°C; bottom is hours of PMV >0.5.

3.3.3. The impact of random sampling within the weather generator

Running the UKCP09 weather generator once has the potential to produce 3,000 synthetic future weather years for one location. However, each iteration of the UKCP09 weather generator does not provide exactly the same future weather data for the same location due to the random sampling method employed when generating weather data. In order to see if this was a concern, we created two different future weather datasets for Norwich in 2050s under the high emission scenario to examine the impact of random sampling of the UKCP09 weather generator. In Figure 3-10 and Figure 3-11, pTRY, pHSY-1 and pHSY-2 in group (a) were created based on the weather data from an initial run of UKCP09 weather generator, whereas group (b) are from a second run of the weather generator. The four assessment metrics were used to examine both groups of weather files.

Figure 3-10 presents overheating risk from the 10th, 50th and 90th percentile TRY, HSY-1 and HSY-2 in both groups using assessment metric (1) and (2). WCDH and hours >28°C calculated from the 10th percentile HSY-2 in group (a) are substantially greater whereas in group (b) are fewer than the 10th percentile TRY. However, WCDH and hours >28°C calculated from the 10th, 50th and 90th percentile HSY-1 in both groups are constantly greater than these from pTRY. Furthermore, the absolute differences of pHSY-1 between group (a) and group (b) are small compared with those of pHSY-2.

Figure 3-11 reveals discomfort hours from the 10th, 50th and 90th percentile TRY, HSY-1 and HSY-2 in both groups using assessment metric (3) and (4). The differences of hours of PET >23°C and PMV >0.5 between group (a) and (b) are -10% and -13% for 10th percentile HSY-2, -4% and -4% for the 50th percentile HSY-2, -4% and -8% for 90th percentile HSY-2 respectively. It indicates that the differences from iterations of UKCP09 weather generator have little impact on the low to high percentile HSY-2 when using assessment metric (3) and (4). It can also be seen that hours of PET >23°C and PMV >0.5 produced by the pHSY-2 in both groups are always greater than the pTRY. The pHSY-1 in group (a) and (b), however, fail to produce more discomfort hours than the pTRY. For instance, the 10th percentile HSY-1 in group (a) shows greater but in group (b) fewer hours of PET >23°C than the 10th percentile TRY; the 90th percentile HSY-1 in group (a) shows fewer but in group (b) more hours of PMV >0.5 than the 90th percentile TRY. The relative differences of the 90th percentile HSY-1 between the two groups are 60% and 43% which are significantly high compared with 90th percentile HSY-2.

In short, WCDH and hours >28°C given by the pHSY-1 as well as hours of PET> 23°C and PMV >0.5 given by pHSY-2 are not influenced by the random sampling method of UKCP09 weather generator.

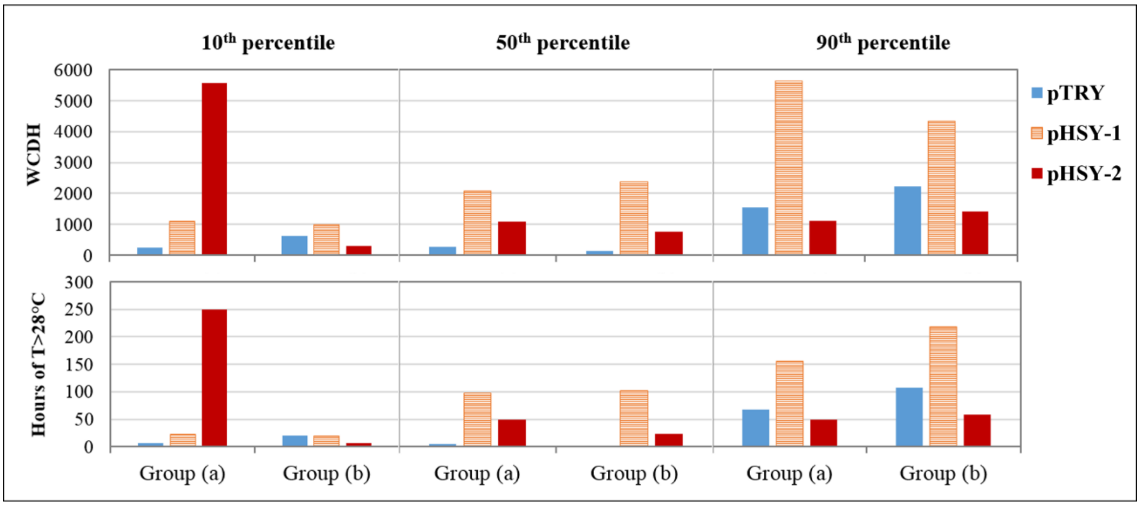


Figure 3-10. Summer overheating hours in Norwich caused by the 10th, 50th and 90th percentile TRY, HSY-1 and HSY-2 in group (a) and in group (b).

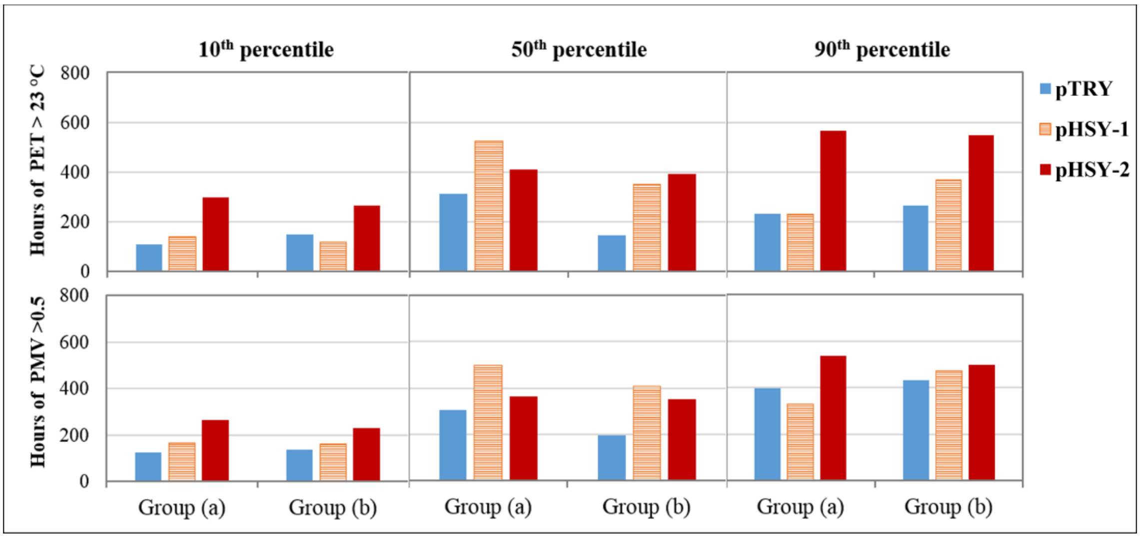


Figure 3-11. Summer thermal discomfort hours in Norwich caused by the 10th, 50th and 90th percentile TRY, HSY-1 and HSY-2 in group (a) and in group (b).

3.4. Engineering choices

As the method outlined can produce probabilistic weather files, the engineer needs to select which percentile to model with. There would be an argument against providing probabilistic future weather files since building designers might prefer to use a deterministic one per location to do overheating risk assessment. However, there are inevitable uncertainties in the climate models due to the limitation of the current understanding on climate change. In order to solve this problem, it would be better to provide probabilistic future weather years to do risk-based assessment. As suggested earlier, this will in part depend on the building and the client. The 90th percentile HSY-1/2 represents a situation that is only predicted to be exceeded by approximately 10% of current predictions of future climate. The 50th percentile HSY-1/2 can be seen as representing the median predictions of climate models with respect to extremes, and the 10th percentile as a situation exceeded by all but 10% of predictions of the extremes. In section 3.3.2 it was shown that the percentiles follow a logical order. Figure 3-12 shows the situation in more detail. Here WCDH and hours >28°C are shown for pHSY-1, and hours of PET >23°C and PMV >0.5 for pHSY-2, with p ranging from 10th to 90th in ten steps. Linear regression between hours >28°C and WCDH for pHSY-1 gives an R^2 of 0.90; while between hours of PMV >0.5 and PET >23°C gives an R^2 of 0.84. So, as one might expect, the metrics are highly correlated. Looking at how all four metrics change with percentile, we have Table 3-5. Although the correlation coefficients are all substantial, and for WCDH and hours of PET >23°C, in all cases, an increase in percentile gives an increase in value (i.e. both are monotonically increasing functions), for hours over 28°C and PMV this monotonic behaviour cannot be guaranteed. However it is true at the larger scale. It would therefore seem sensible to recommend that in engineering studies a maximum of a low, medium and high percentile are used (probably 10th, 50th and 90th percentiles).

Table 3-5. R^2 with respect to percentile for the four metrics

	WCDH	hours >28°C	Hours of PET >23°C	Hours of PMV >0.5
R^2	0.94	0.90	0.99	0.87

In any practical application whether pHSY1 or pHSY2 is used will depend on the way overheating is to be assessed. If a simple traditional metric (such as hours above a set temperature) is to be used then pHSY1 would be more appropriate. If however a more complex metric (such as PMV) is to be used pHSY2 would be more sensible and robust.

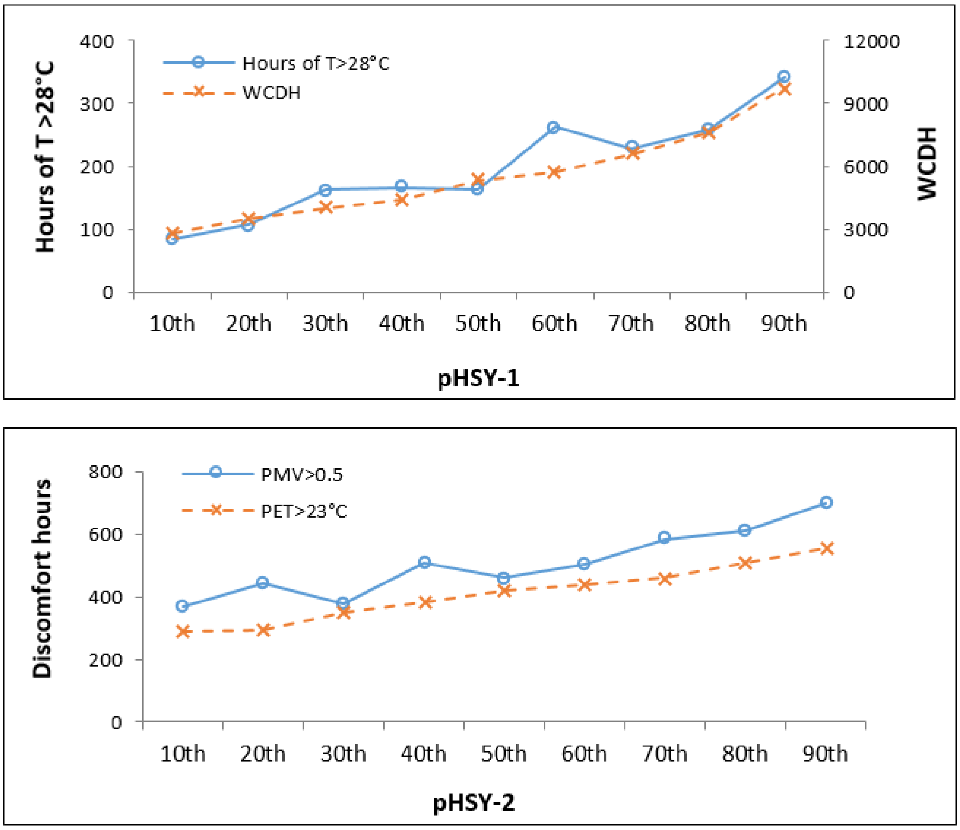


Figure 3-12. Overheating hours and discomfort hours with increasing percentile HSY-1 and HSY-2 for London.

3.5. Conclusions

This study proposes two new approaches for the creation of future summer reference years to assess overheating risk and thermal discomfort under a changing climate. The future pHSY-1 was created based on the ascending order of WCDH while future pHSY-2 was created based on ascending order of hours of PET >23°C. The use of WCDH for pHSY-1 highlights weather years with periods of high temperatures, which have the potential to cause significant overheating in buildings, as measured using traditional simple metric. The pHSY-2 is based upon PET, which highlights weather years which will have a significant impact upon human thermal comfort. It should be noted that both pHSY-1 and pHSY-2 represent the non-extreme but hot summer years. In consistent to the usage of CIBSE DSY, the pHSY-1 and pHSY-2 are used for assessing the risk of overheating and discomfort hours during all summer (April to September) rather than an extreme hot event such as heatwave. It is as yet unknown how to create future heatwaves which is critical to death. According to the Environmental Health Perspectives and the National Institute of Environmental Health Sciences , however, the increased average temperature also has a great influence on the heat-related illness. Thus, pHSY-1 and pHSY-2 might not be suitable for indicating heat-related death but potential morbidity and mortality. They have been compared to the existing future pTRY and pDSY for fourteen sites around the UK using a conceptual reference building and four different assessment metrics. The results from the investigations could be summarised as follows.

(1) We find that the pHSY-1 consistently indicates greater WCDH and hours >28°C than the equivalent pTRY and the pHSY-2 consistently indicates more hours of PET >23°C and PMV >0.5 than the pTRY for all fourteen UK sites. Furthermore we find that the pDSY does not consistently show more overheating or thermal discomfort than the pTRY, likely due to the simple selection methodology.

(2) WCDH and hours >28°C increase with increasing percentiles for the pHSY-1. Similarly, higher percentiles of HSY-2 consistently produce more hours of PET >23°C and PMV >0.5. We find a linear relationship (R^2 = 0.92) between WCDH and hours >28°C for the pHSY-1. It has been shown that PET >23°C is comparable to PMV >0.5 (Matzarakis and Mayer, 1996); here, we found a close linear relationship (R^2 = 0.88) between the hours of PET >23°C and hours of PMV >0.5 for pHSY-2.

(3) According to the comparison between group (a) and group (b), any variation due to the random sampling method used by the UKCP09 weather generator has little impact on

WCDH and hours >28°C given by pHSY-1. Similarly, its influence on hours of PET >23°C and PMV >0.5 calculated from pHSY-2 are negligibly small.

(4) The results presented in this paper highlight an important limitation of using different metrics to compare overheating years. If the weather year is created based upon ranking of a single environmental variable such as temperature then assessment should be with similar metrics (e.g. hours >28°C or WCDH), if the weather year is based upon several environmental variables then a composite metric is required (e.g. PMV or PET). Using inappropriate metrics produces inconsistent results. This has important implications for the suitability of different weather files for either overheating or thermal comfort analysis.

From the above discussion, pHSY-1 could be used for determining the occurrence of overheating based on a benchmark peak summer temperature (e.g. 28°C as recommended in CIBSE Guide A (CIBSE, 2006a)). It would also be appropriate to use pHSY-1 for assessing the severity of overheating based on the WCDH, which has greater emphasis on the higher summer temperature. Thermal comfort however, relies on several weather parameters including temperature, air movement and humidity. The pHSY-2 could therefore be used to assess the thermal discomfort or heat stress based on a thermal index such as PET or PMV. These thermal indices can indicate the level of heat stress (Matzarakis and Mayer, 1996 (Matzarakis and Mayer, 1996)) which is of importance to human health and well-being. CIBSE Guide A (CIBSE, 2006a) simply recommends that hours of operative temperature above 28°C should not exceed 1% of annual occupied hours in living room. However, there are so far no criteria based upon the thermal index that defines whether a building is thermally acceptable or not. It is therefore suggested research on an alternative thermal comfort standard based on thermal index (e.g. a limit for the number or fraction of occupied hours with PMV >0.5) is required.

4. Creation of Realistic Dwelling Models

This chapter describes how thermal models based on the measured building information and local shading were created. The reasons for using two dynamic thermal modelling packages are listed in section 4.1; the fifteen basic thermal models, i.e. five UK typical dwelling types each with three predominant construction types, one ventilation strategy, one occupancy profile and internal gain settings are presented in section 4.2; the methodology for remote building measurement is illustrated in section 4.3; geometries of the basic thermal models were augmented with the measured building information and local shading, which are described in section 4.3.

4.1. Thermal modelling tool

Dynamic thermal modelling cannot guarantee more precise results due to the inevitable uncertainties caused by lack of building information and imperfect understanding of thermal processes in buildings. It is also more complex and time-consuming than static thermal simulation. However, dynamic thermal simulations can provide sub-hourly outputs by considering transient heat balance. Furthermore, most of the dynamic building simulation packages mentioned in 2.3.2 have already incorporated static and adaptive thermal comfort assessment metrics and functions for various thermal comfort indices, which can facilitate the assessment of overheating risk. Moreover, dynamic thermal simulation is capable of modelling the effect of natural ventilation which is of importance to the indoor thermal environment. Most importantly, the hourly/sub-hourly outputs of dynamic thermal simulation can be used to explicitly quantify both the duration and the severity of overheating.

In this study, a large number of dynamic thermal models of dwellings are required in order to investigate the spatial variation in overheating due to the variability in the dwelling characteristics. Among the dynamic thermal simulation packages, the combination of EnergyPlus and DesignBuilder have been deployed due to the reasons as follows:

(1) EnergyPlus is an acknowledged well-known dynamic thermal simulation package with a powerful simulation engine but its user interface is not friendly, especially for geometry modelling.

(2) DesignBuilder provides a user-friendly interface including a powerful 3-D geometry modelling module and a database of the building materials, construction components,

occupancy profiles, internal gains, etc. for a selected country, which can substantially facilitate the thermal modelling process.

(3) DesignBuilder’s simulation engine is the same as the EnergyPlus’s. Nonetheless, there are a few limitations in its modelling capabilities. For example, DesignBuilder offers specific metabolic rate depending on the selected activity level but it does not allow editing the personal metabolic rate. DesignBuilder can export the thermal models as the EnergyPlus Input Data Files (IDFs) for further editing by EnergyPlus IDF-Editor which can edit details such as personal metabolic rate.

(4) Unlike DesignBuilder files, IDF is a structured text file (including building description and weather data) which is free to access and easy to write and read. Thus, IDFs can be edited with programming languages such as MATLAB and Python. This is important to this study as the fifteen basic dwelling models (see section 4.2) can be automatically augmented with building information of an approximately a thousand real dwellings and their local shadings measured in a city.

4.2. Basic dwelling models

4.2.1. Geometry and construction

The five typical UK dwellings: detached house, semi-detached house, terraced house, flat and bungalow have been selected as illustrated in Figure 4-1. The basic geometry information of the five UK dwelling types is from BEPAC Technical Note (Allen and Pinney, 1990) and the PhD thesis written by Porritt (2012) with a few modifications. Dwelling geometry, floor plan including areas of the living room and the main bedroom, and 3-D views for each dwelling type can be found in Appendix A.

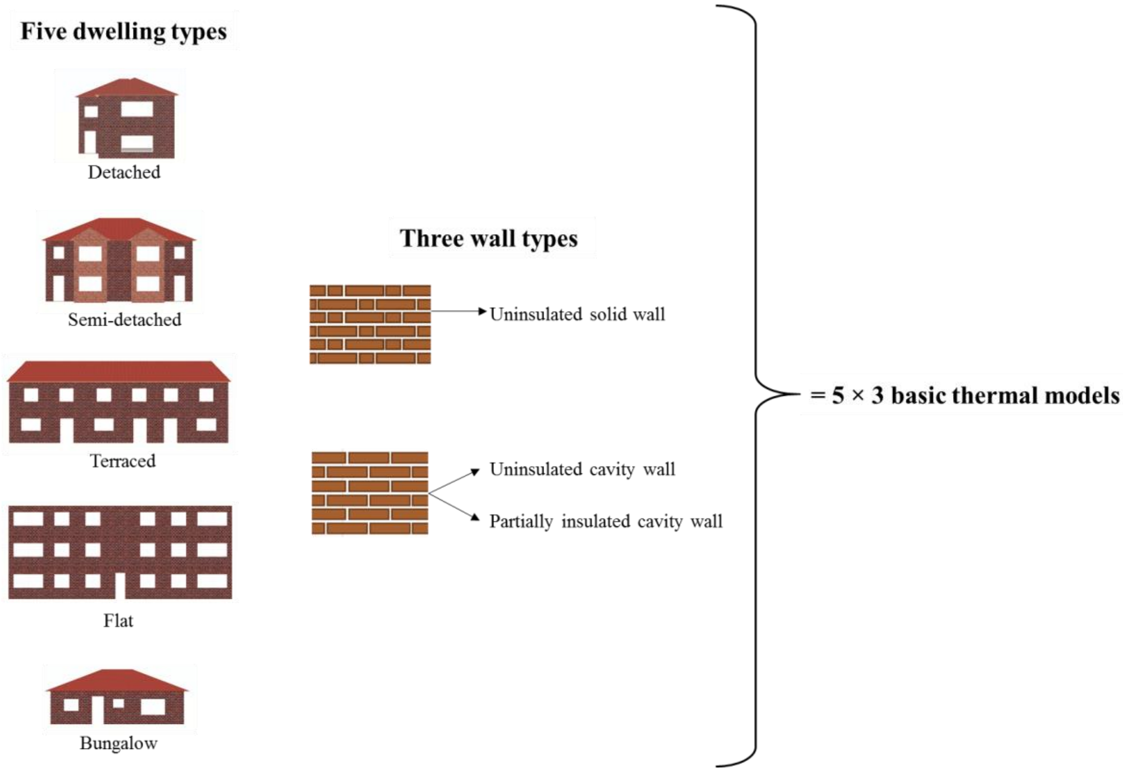


Figure 4-1. Five dwelling types each with three wall types.

According to the EHS Headline Report 2014-2015 (DCLG, 2016), wall types for the dwellings can be divided into solid and cavity walls. Wall insulation for dwellings has been significantly improved since 1996 due to government initiatives to improve the energy performance of buildings. By 2014, approximately 48% of English houses had improved wall insulation; 69% of cavity walls and only 9% of solid walls had been insulated (DCLG, 2016). As shown in Figure

4-1, three predominant external walls: uninsulated solid wall, uninsulated cavity wall and partially insulated cavity wall (see Table A-1 in Appendix A) have been defined for each of five UK dwelling types. It was assumed that the insulation levels for the ground floor and the roof are consistent with the external wall insulation levels. Likewise, single glazing with wooden window frame was installed for the uninsulated houses while double glazing with uPVC window frame for the insulated houses. In addition, two types of internal partitions, i.e. heavyweight and lightweight have been selected based on the wall types; for instance, heavyweight for the solid wall houses while lightweight for the cavity wall houses. In total, fifteen basic dwelling models (see Figure 4-1) were created prior to applying measured building information. The typical construction details and U-values, properties of construction materials and window characteristics are presented in Appendix A. These were selected from DesignBuilder construction library as well as Appendix 3. A8 in CIBES Guide A (CIBSE, 2006a). Note that the U-values of three external walls are consistent to the values presented in Table S6 in RdSAP Appendix S (BRE, 2005) which contains U-values of walls from a site survey of English housing stocks.

4.2.2. Natural ventilation

As mentioned above, modelling natural ventilation is highly important to the assessment of overheating risk. DesignBuilder provides two natural ventilation model options: ‘Scheduled’ and ‘Calculated’. The scheduled ventilation option sets a fixed natural ventilation flow rate (i.e. air change rate) for a given zone area to model the ventilation and infiltration while the calculated ventilation option uses EnergyPlus Airflow Network Model (Gu, 2007) to calculate an instantaneous natural ventilation flow rate per zone area based on the airtightness, opening area, wind and buoyancy pressure, natural ventilation set-point temperatures, etc. If typical natural ventilation rate of a house is available, scheduled ventilation option is recommended to use as it is simple and much faster than the calculated natural ventilation simulation. Nevertheless, calculated ventilation option was used in this study. First and foremost, calculated ventilation is more accurate than the scheduled ventilation; besides, typical natural ventilation rate is not available from remote dwelling measurement (see subsection 4.3.1) so that it has to be calculated. The remote dwelling measurement includes the openable area of the window but the information about cracks, i.e. the airtightness. DesignBuilder provides five crack templates each representing ‘Very poor’, ‘Poor’, ‘Medium’, ‘Good’ and ‘Excellent’ airtightness. Poor airtightness was set for uninsulated houses and good airtightness for insulated houses in this study. In addition, 0.65 was set as a standard discharge coefficient for cracks, as recommended by DesignBuilder.

DesignBuilder also provides wind pressure coefficient templates which have been set based on the database from The Air Infiltration and Ventilation Centre (Liddament, 1986). The EnergyPlus Airflow Network Model uses wind pressure coefficient, which is a function of wind speed, direction and position of the exposed wall, to calculate wind induced pressure which is a key element for natural ventilation rate calculation. Due to the detailed and complex natural ventilation rate calculation, calculated ventilation option makes dynamic thermal simulation computationally expensive. Such issues, however, were mitigated in this study through the use of University of Bath's High Performing Computing system.

Natural ventilation in houses is mainly driven by opening windows. It was assumed that window is open during occupied hours when the internal temperature is higher than 24°C, and external temperature is lower than internal temperature.

4.2.3. Occupancy and internal gains

It is true that the occupancy and internal gains have a great impact on indoor thermal comfort. However, the remote dwelling measurement (see subsection 4.3.1) cannot include information about occupancy and internal gains. This study tried to find out the relative impact of dwelling types and localised weather conditions on spatial variation in the risk of overheating rather than predict absolute overheating risk for a region. Hence, the occupied hours and internal gains for all dwelling types were assumed to be the same. The occupied hours for the living room (08:00 to 22:00) and the main bedrooms (23:00 to 07:00) are consistent with those given in a UK national survey (Beizaee *et al.*, 2013) and previous modelling-based overheating risk studies (Porritt *et al.*, 2012; Taylor *et al.*, 2014; Gupta and Gregg, 2013; Porritt, 2012). The number of occupants was assumed to be equal to the number of bedrooms plus one indicating a couple in the main bedroom. In addition, one adult is assumed to be working while the other stay in the living room during the daytime in order to calculate overheating hours for the living room taking account of operation of natural ventilation which is only triggered during occupied hours. Table 4-1 shows occupancy profile used in thermal modelling. Like the creation of basic UK dwelling geometries, occupancy profile including activity and occupants' heat generation were constructed based on the recommendations from BEPAC Technical Note (Allen and Pinney, 1990) and the PhD thesis written by Porritt (2012). The metabolic rates were originally derived from Table 1.4 in CIBSE Guide A (CIBSE, 2006a). Regarding internal gains from equipment and lightings, 3.9W/m^2 and 3.58W/m^2 have been used for living room and the main bedroom respectively. DesignBuilder considers them as standard values for UK housing stocks; in addition, these values are consistent with the outputs of domestic electricity demand model created by Richardson and Thomson (2010).

Table 4-1. Occupancy profile

Rooms	**Occupant time**	**Activity**	**Metabolic rate^a)^ (met)**	**Heat generation^b)^ (W/person)**	**Number of occupants**
Main bedroom	23:00 to 08:00	sleeping	0.7	68	2 people
Bedroom	17:00 to 1800 19:00 to 23:00	reading, writing sleeping	1.0 0.7	78 55	1 person
Living room	09:00 to 17:00 17:00 to 22:00	seated or standing seated or standing	1.0 1.0	100 106	1 person 2 people
Kitchen	08:00 to 09:00 18:00 to 19:00	cooking	2.0	177	1 person
Dining room	08:00 to 09:00 18:00 to 19:00	eating and drinking	1.9	166	The whole family
Bathroom	08:00 to 09:00 22:00 to 23:00	Standing, relaxed Standing, relaxed	1.2 1.2	105 105	1 person
Hall and landing	08:00 to 09:00 17:00 to 18:00	walking (0.9 m/s)	2.0	175	1 person

Note: a) The metabolic factors of 0.85 and 0.75 suggested by DesignBuilder software have been used for a woman and child when calculating heat generation (W/person); b) The averaged heat generation of all occupants.

4.3. Modelling local dwellings

Dwelling characteristics such as wall types, window types, glazing ratio and openable area, and local shading have a great impact on indoor thermal comfort. Nonetheless such important dwelling information for thermal modelling at a large scale (e.g. citywide scale) is rare as mentioned in subsection 2.4.4 and 2.6.4. Real dwelling characteristics are essential for this study which aimed to investigate the spatial variation in overheating attributable to variability of local dwellings. It is true that on-site measurement of housing stocks for the purpose of constructing a complete set of inputs for dynamic thermal models is expensive and time-consuming. To obtain such information for a large number of local dwellings, therefore, was a great challenge for this study. An efficient way of remote dwelling measurement is introduced in subsection 4.3.1. The method for creating a great number of realistic thermal models each based on measured dwelling information is described in subsection 4.3.2.

4.3.1. Remote dwelling measurement

Ramallo-González (2015) developed a remote window survey tool which utilises Google Street View® with Google Maps®. Thus, the tool is applicable anywhere that these services can provide imagery for. This tool has been upgraded by adding functions to measure additional dwelling characteristics. The measurement includes dwelling types, orientations, local shadings (i.e. obstruction angles (Littlefair, 2011)), external wall dimensions and types (e.g. solid or cavity wall), window dimensions, glazing types (e.g. single or double) and ratios (i.e. % of glazing area to external wall area), opening types (e.g. casement, single hung, awning, hopper, slider) and ratios (i.e. % of openable area to external wall area). Users need to manually select dwelling types, wall areas and types, glazing areas and types, opening areas and types. The remote survey tool can save users' selections and automatically calculate the glazing ratios and opening ratios. The figures below show the remote measurement of a mid-terraced house located in Sheffield. The dwelling type can be recognised from Google Street View® as shown in Figure 4-2. The glazing types can be inferred from the window frame as, in general, wooden framed windows are single glazed while uPVC framed windows are double glazed. Wall types can be recognised from the pattern of brickwork (see Figure 4-1). As shown in Figure 4-2 and Figure 4-3, the mid-terraced house installed cavity wall and double glazing windows with the uPVC frame; the window opening type is awning. Figure 4-4 shows the measurement of building orientation and obstruction angle, and Figure 4-5 presents the real dimensions of external wall area, glazing area and openable area. The wall with the main entrance door was considered as the front wall of the house; then the orientation of the front wall was measured. The external wall, glazing and openable areas need to be manually and precisely selected with four points, i.e. four corners. In addition to the real dimensions, the remote window survey tool calculates glazing ratios and opening ratios which are particularly important to the creation of the realistic thermal models.

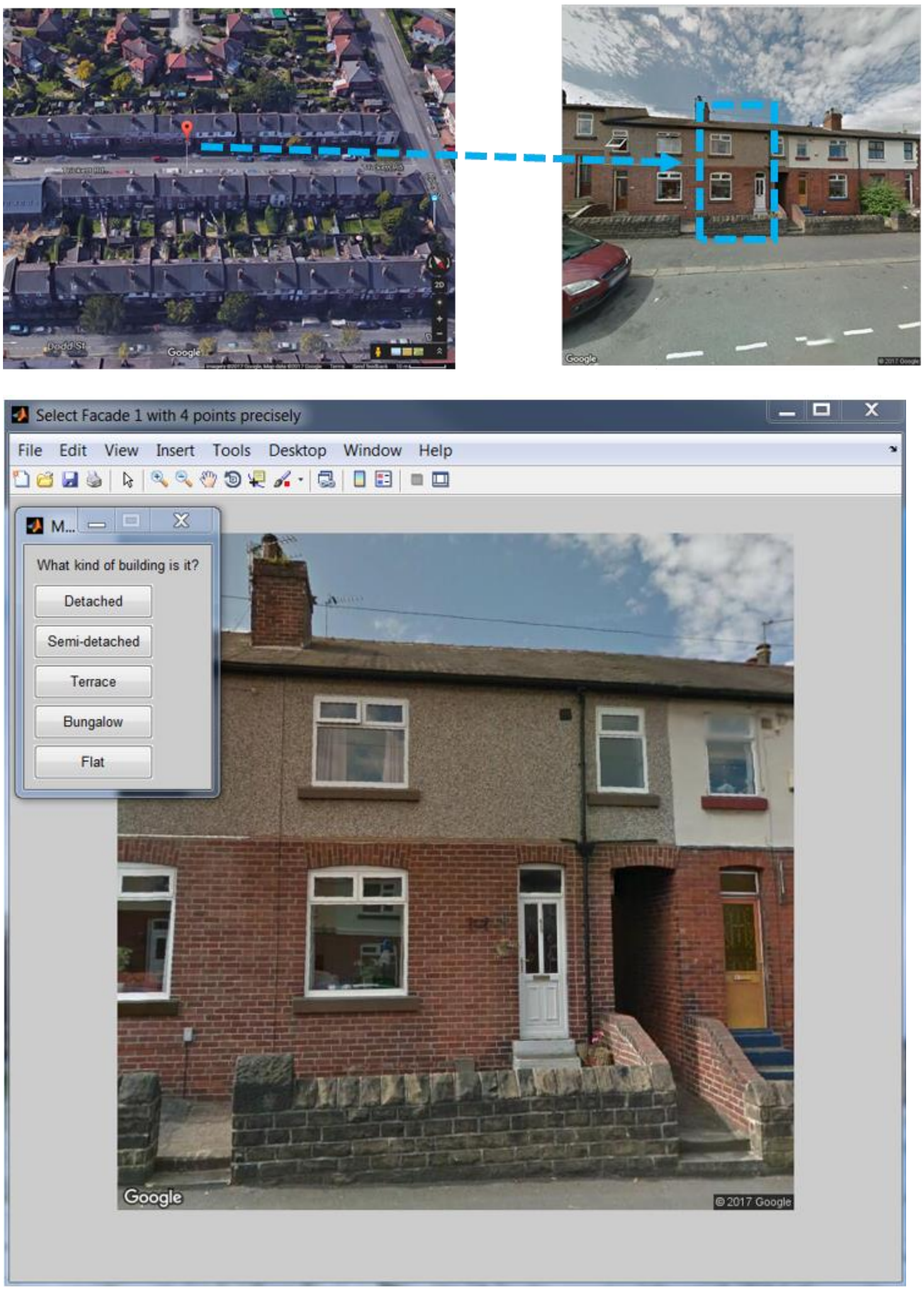
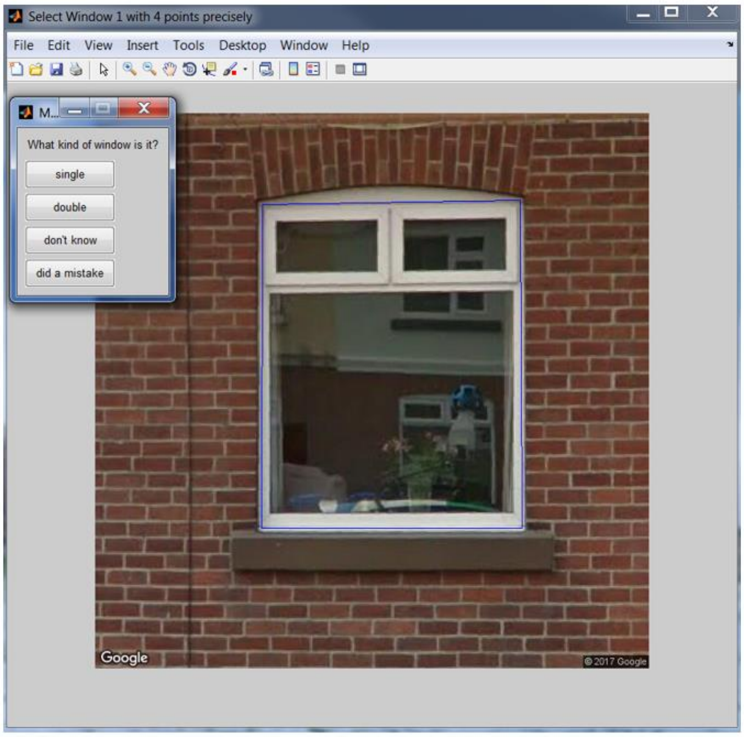


Figure 4-2. Dwelling type identification.



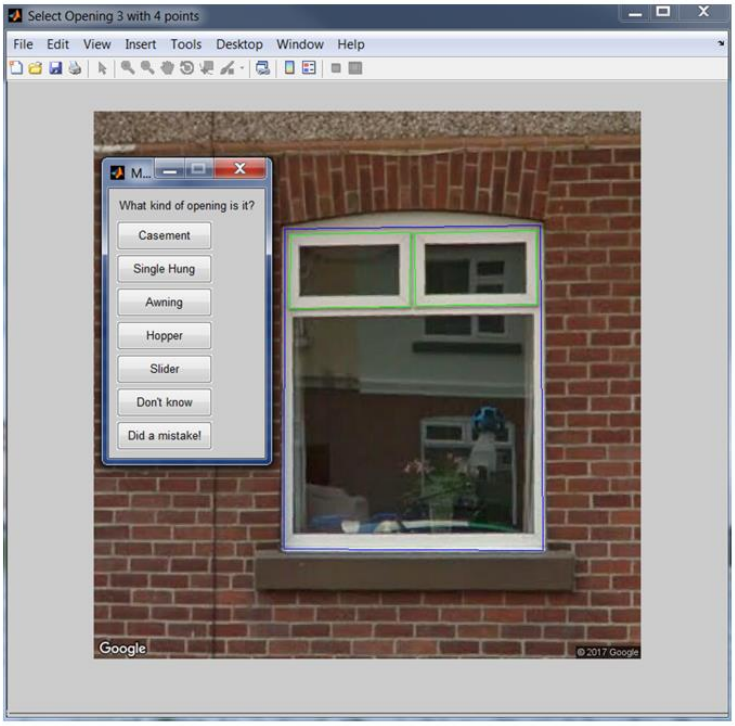
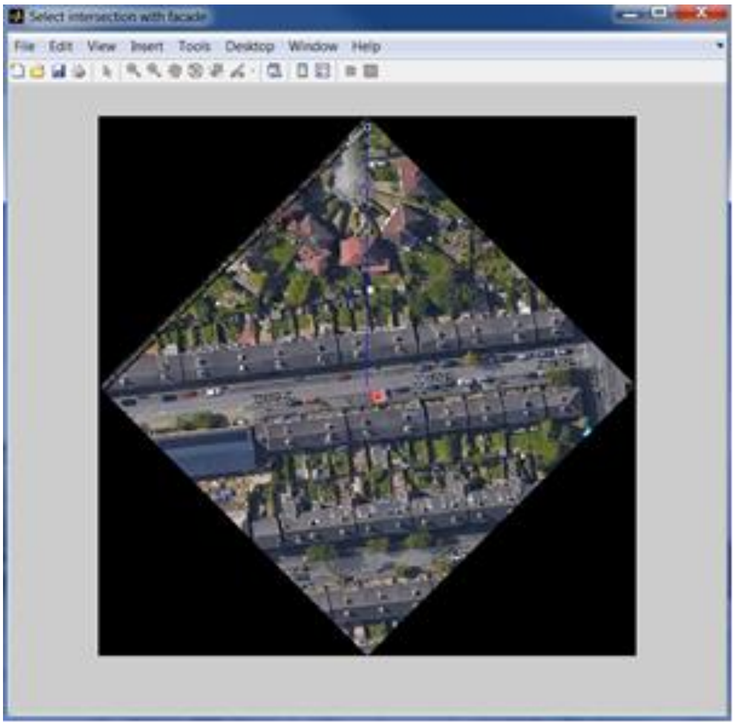
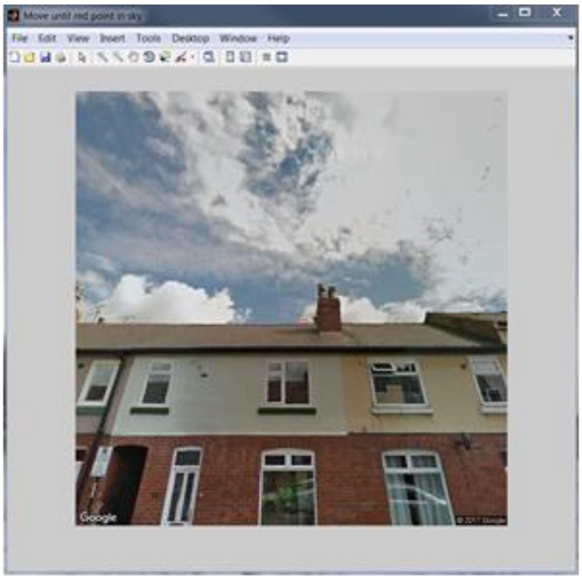
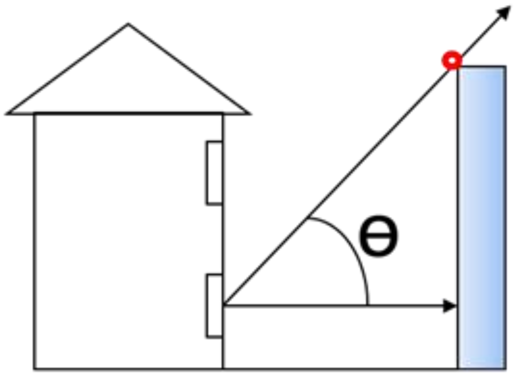


Figure 4-3. Identification of the window type, opening type, and external wall type which can be recognised from the pattern of brickwork. The window area is shown as blue outline while the openable area is shown as green outline.



a) Orientation





b) Obstruction angle

Figure 4-4. Building orientation and obstruction angle measurement. a) shows the orientation of the terraced houses, the row of which is approximately 38° from North (blue line); b) shows the obstruction angle (ϴ) which is approximately 50° measured from the middle of the first floor window; the red circle is the highest point of the house on opposite side.

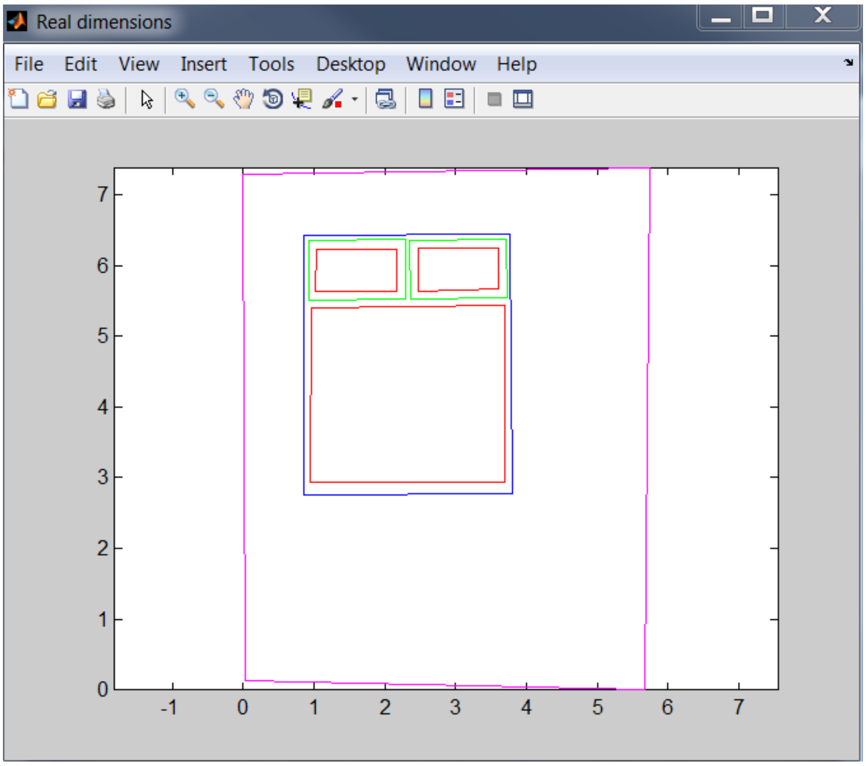


Figure 4-5. Real dimensions of the external wall (purple), window (blue), glazing (red) and opening (green).

As the synthetic weather data from the UKCP09 WG is available at 5km by 5km grid resolution over the UK, a medium-large UK city was selected and divided at the same grid resolution (see Figure 5-1). For the first time, dynamic thermal models were created based on the measurement of dwellings found in every single grid square of a city. The sample size for the dwellings in each grid square was calculated using the equation 5-1. A sample size of 68 for each grid square was determined given a confidence level of 90% and a margin error of 10%. There were fewer than 68 houses in the rural area of the city. All of the houses found in such grid squares were measured. Hence, the sample size across the city was not uniform as shown in Table 5-1.

4.3.2. Creation of thermal models

The fifteen basic dwelling models (i.e. 5 dwelling types × 3 construction types as illustrated in Figure 4-1) combined with the measured dwelling characteristics and local shadings have been used to create thermal models of local dwellings. A few assumptions have to be made on unavailable dwelling characteristics. For instance, the glazing type and ratio, opening type and ratio for the rear façades of dwellings are not available since the Google Street View® only provides images for the front facades of dwellings that face the street. Thus, glazing and opening types for the rear windows were assumed to be consistent to the front windows while the glazing and opening ratios for the rear facades were estimated according to the comparison between the values of the basic dwelling model and the measured values. In addition, the remote measurement did not include the wall insulation but wall types (i.e. solid or cavity) which can indicate the wall insulation. As mentioned in subsection 4.2.1, only 9% of the solid walls are insulated according to the EHS Headline Report 2014-2015 (DCLG, 2016); hence, all of the measured solid walls were assumed to be uninsulated. The appearance of dwellings can help with identifying cavity wall insulation. It was assumed that new dwellings with cavity wall were insulated while old dwellings were not; meanwhile, the percentage of measured cavity walls with insulation among the random dwelling measurements for a case study city was made equal to 69% which was consistent to that of the EHS Headline Report 2014-2015 (DCLG, 2016). Moreover, local shadings, which have been paid little or no concern in previous research, was modelled based on the measured obstruction angle. As illustrated in Figure 4-4, an adiabatic wall was installed in front of the dwelling to represent the local shadings. The height of the adiabatic wall was calculated based on the obstruction angle.

A few assumptions had to be made on unavailable dwelling information due to the limitations of the remote survey tool. However, the remote dwelling measurement included elements such as dwelling types, wall types, glazing and opening types and ratios which are key to the thermal modelling for the naturally ventilated dwellings. Therefore, the proposed approach to thermal modelling can account for more realistic variability of local dwelling characteristics compared to the previous modelling based studies.

5. High Resolution Mapping of Overheating and Mortality Risk

The content of this chapter is from a paper entitled 'High Resolution Mapping of Overheating and Mortality Risk' which has been published in the journal of Building and Environment. The authors are C. Liu, T. Kershaw, D. Fosas, A.P. Ramallo Gonzalez, S. Natarajan and D.A. Coley. Regarding this paper, the statement of authorship form and evidence of permission can be found in Appendix D and E respectively. The data access of this academic paper is shown in the results section.

The pHSY-1 proposed in chapter 3 has been used in this chapter to assess the occurrence and severity of overheating, and potential heat-related mortality. A statistical method combined with a new remote surveying tool has been used to assemble accurate models of real buildings across a landscape. This chapter presented maps of overheating and heat-related deaths now and in the future at a resolution of 5km x 5km. High spatial variation in the risk of overheating and heat-related mortality was found due to the variability of architecture, context and weather. Variability from the architecture and shading context were found to be a greater influence on the spatial variation in overheating than climate variability. Overheating risk was found to increase significantly with heat-related mortality tripling by the 2050s. The method was validated against data collected during the northern hemisphere 2006 hot summer. The maps produced would be a highly useful resource for government in identifying populations of greatest concern when developing policies to combat such deaths.

5.1. Introduction

Despite international efforts to combat global warming since the Rio Earth Summit in 1992 (United Nations, 1992), global surface temperatures are projected to rise by up to 4.8 °C by the end of this century (IPCC, 2013). Such warming increases the risk of overheating in non-air-conditioned buildings; a risk which might be further exasperated by fabric improvements (Hajat *et al*., 2014). In August 2003, 14,729 excess deaths occurred in France (Fouillet *et al*., 2006) and 2,139 in England and Wales, due to a severe heat wave, primarily in large urban centres (Johnson *et al*., 2005). Interestingly, it was found that the top floor presented a higher risk of heat-related mortality, and lack of home insulation was one of the major risk factors for the excess deaths

(Vandentorren *et al*., 2006). This indicates that architectural detail and lack of shading are both risk factors in such mortality.

Unfortunately, many weather events that are currently classed as extreme will become more frequent as a result of climate change. For instance, it is reported that the frequency and duration of heat waves are very likely to increase during the 21st century (IPCC, 2013), with the heat wave of 2003 representing a typical summer by the 2040s, and heat related deaths tripling by the 2050s (Hajat *et al*., 2014). Indeed, it is estimated that human activities have already increased the likelihood of a 2003 type event from one in several thousand to ~1:100 in little over a decade (Christidis *et al*., 2015). Looking further into the future, heat related deaths are predicted to increase 5-fold under a medium carbon emission scenario (SERS A1B), by the 2080s (Hajat *et al*., 2014). A first step to avoiding such deaths and providing occupants with a comfortable indoor environment is a locally-relevant assessment of overheating risk which takes climate change into account.

There have been several general different assessments of future overheating risk, using dynamic thermal models of buildings and future weather files, and all show that overheating risk is on the rise. (McLeod *et al*., 2013; Gupta and Gregg, 2012; Jentsch *et al*., 2008; Jenkins *et al*., 2011; Frank, 2005; Coley *et al*., 2012; Demanuele *et al*., 2012; Jenkins *et al*., 2014; Tian and de Wilde, 2011; de Wilde and Tian, 2009, 2010; Gupta and Gregg, 2013; Peacock *et al*., 2010; Mavrogianni *et al*., 2012). Appropriate weather files are the prerequisites for any reliable thermal simulation. These take various forms in various parts of the world, for example Test Reference Years (TRYs) and Design Summer Years (DSYs); however, these are normally on too coarse a spatial grid to be locally accurate (CIBSE, 2013c). Previous research (Eames *et al*., 2012a) which simulated indoor environmental conditions for different locations across two regions with varying topography, using weather files at a spatial resolution of 5km found that there are distinct variations in overheating risk with location, especially in regions with large topographic differences. Hence it is possible to conclude that location-specific (future) weather data is required to perform accurate overheating risk assessments of populations. Although Eames *et al*. (2012a) used weather files at a high spatial resolution, they failed to take into account any variability in the building characteristics and urban form.

It is well known that the presence and form of surrounding buildings can have a major impact on overheating risk due to mutual shading and radiative exchange (Futcher *et al*., 2013). The materials used and the architectural form will also have a considerable impact, particularly the thermal mass and the glazing ratio. Hence an accurate assessment would require building information about a large number of buildings across the study area. It is however, not easy to find sufficient building information containing all the necessary variables required for thermal modelling at a large scale. Examples such as housing surveys (DCLG, 2015), energy follow-up surveys (DECC, 2013) and energy efficiency databases (EST, 2013), etc. provide nationwide building information, but none of these datasets are primarily collected for the purpose of thermal modelling (DCLG, 2015). Hence there is a lack of information regarding building orientation, local shading and glazing ratios (Taylor *et al*., 2014; Porritt *et al*., 2012; Futcher *et al*., 2013), i.e. they lack context. This has led to there being very few studies that model a large number of real existing buildings individually; instead representative or archetype models of dwelling types have been used with little to no concern of, for example, the surrounding obstructions or how built form, or density, changes across a region or country (Gupta and Gregg, 2012; Mavrogianni *et al*., 2012; Gupta and Gregg, 2013; Taylor *et al*., 2014; Oikonomou *et al*., 2012; Taylor *et al*., 2015).

This study focuses on current and future spatial variation in overheating risk and heat-related mortality across a landscape. A new method is developed and then applied to a representative medium-large mid-latitude city with large topographic and density differences, and the results validated against calculated excess mortality from measured temperatures in London during 2006. As mentioned above, the problems for such a large scale overheating risk assessment are lack of detailed building information and unrepresentative weather years. These problems have been solved in this study by modelling a large number of randomly selected real dwellings sitting in their real surroundings and the use of probabilistic Hot Summer Years (pHSYs) (Liu *et al*., 2016) at a resolution of 5km. In total, 907 distinct thermal models have each been simulated with 100 pHSYs, resulting in 100 probabilistic projections of overheating risk per dwelling for the current climate i.e. 2020s (2010 - 2039) and a possible future climate scenario for the 2050s (2040 - 2069). Maps of the distribution of the overheating risk and the expected heat-related mortality rate across the study area have then been created.

5.2. Methodology

Sheffield (53.38° N, 1.47° W) was selected as the study area. Sheffield covers an area of 367.94 km^2 and is the 5th largest city in the UK. There are approximately 553,000 people and 237,000 dwellings in the city (ONS, 2011a). The topography varies greatly from east to west, with a National Park bordering the west of the city. The difference in elevation between the east and west areas is around 200 m. Hence, given a surface temperature lapse rate 0.8 °C/100m (Holden and Rose, 2011), there should be approximately a 1.6°C difference in temperature between these two regions. The housing density across the study area varies from fewer than 10 units per km^2 to more than 7,000 per km^2 (URBED, 2015).

5.2.1. Representative weather data

Given sufficient observed hourly weather data from a high spatial resolution network of weather stations and climate projections from either global or regional climate models, it is possible to create future weather data for any location in the world using the morphing methodology (Belcher *et al*., 2005). Such localised observed hourly weather data however, is typically not available, so synthetic weather data has to be used, for example the UKCP09 weather generator (Jones *et al*., 2010) can produce large amounts of synthetic weather data at a 5 km by 5 km resolution for the current century. The UKCP09 weather generator randomly chooses projections of climate change from probability density functions of possible climate change anomalies, and uses these to perturb weather data from a synthetic control period (1961-1990) (Jenkins *et al*., 2009). It can generate weather data for three emission scenarios (SRES B1, A1B and A1FI) and seven overlapping 30-year time periods spanning 2010 to 2099, in addition to control data spanning 1961-1990. A downside of such weather generators is that each grid square is treated independently with no consistency in underlying weather patterns between adjacent grid squares. However, it has been shown that the differences caused by random sampling within the UKCP09 weather generator are much smaller than the differences due to other factors such as topography between adjacent grid squares (Eames *et al*., 2012a). Furthermore, a comparison of future weather data produced by morphing and the UKCP09 weather generator (Eames *et al*., 2012b), concluded that simulations with morphed future weather files could underestimate the total overheating hours, but at the same time overestimate peak temperatures, providing further justification for the choice of synthetic weather data over a morphing methodology. (Note, there have been several different approaches (Eames *et al*., 2011; Watkins *et al*., 2011, 2012; Smith and Hanby, 2012; Jentsch *et al*., 2015; Liu *et al*., 2016) to constructing future weather files for building simulation using the outputs of the UKCP09 weather generator. A review of these different methodologies can be found in the papers written by Mylona (2012) and Liu *et al*. (2016).)

For this study the new probabilistic Hot Summer Years (pHSYs) (Liu *et al*., 2016) have been used. There are 100 sets of 30-year period weather data obtained from each run of the UKCP09 weather generator. The one with the hottest summer was selected from the 30-year period. In total, 100 hottest summer years were selected from 100 sets and they are ranked based on the ascending order of warm summers to produce 1^{st} to 100^{th} percentile HSYs. Two metrics were used for identifying the warmth of a summer so that there were two types of pHSYs: one is based on Weighted Cooling Degree Hours (WCDH) (pHSY-1) and the other is based on the Physiologically Equivalent Temperature (Hoppe, 1999) (pHSY-2). In this paper, pHSY-1 (from now on referred to as pHSY) has been used, as this has been shown to be suitable for assessing the severity of overheating risk (Liu *et al*., 2016). Each run of the UKCP09 weather generator can output 100 sets of equi-probable climate and weather projections and hence 100 pHSYs. For each grid square 100 pHSYs were created for two time periods, the 2020s (2010 to 2039) intended to represent the current hot summer years and the 2050s (2040 to 2069) to represent possible future hot summer years.

The city of Sheffield is covered by eighteen UKCP09 grid squares as shown in Figure 5-1, whilst grid square 0 is within the city's limits, it contains no dwellings and hence no simulations were performed for grid square 0. Using the SRES A1FI emission scenario, 17 sets of 100 pHSYs (1^{st} to 100^{th} percentile HSYs) were produced for the 2020s and 2050s respectively. In total, 3,400 pHSYs (i.e. 100 pHSYs × 17 grid squares × 1 emission scenario × 2 future time periods) were used for this study. The pHSY represent warm/hot summers but are unlikely to include heat waves with a return period of greater than 15 years, hence they are not extreme. With respect to mean summertime air temperature, in this study the 90^{th} percentile pHSY's represented on average the 98th percentile (15°C), and the 50^{th} percentile pHSY's the 90^{th} (14°C) in an ordered list of the weather files used to assemble them in each grid square. With respect to maximum mean three-day air temperature, the 90^{th} percentile pHSY's represented the 94^{th} percentile on average (25°C), and the 50^{th} percentile pHSY's the 77^{th} (24°C).

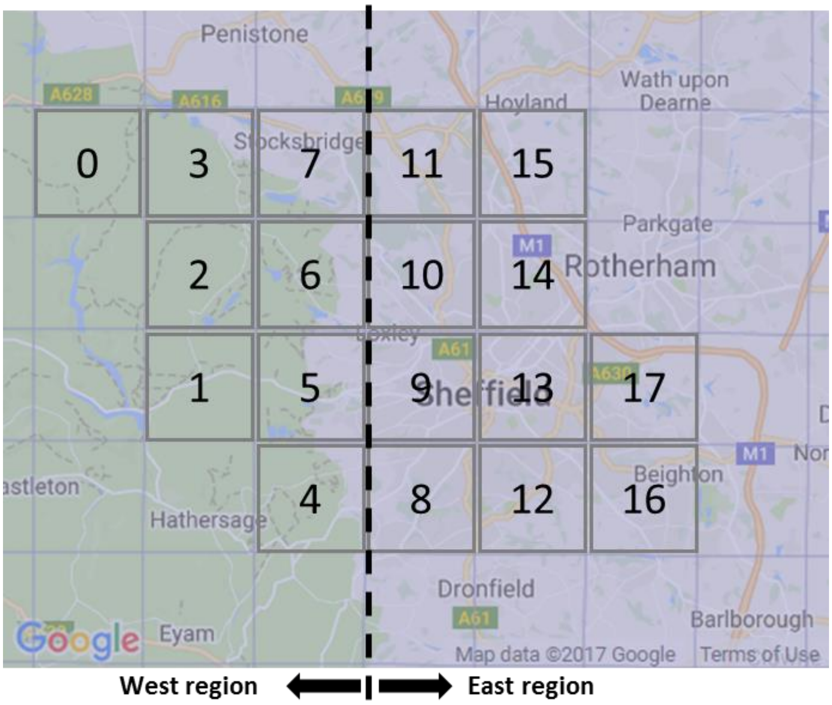


Figure 5-1. Numbered UKCP09 grid squares for the city of Sheffield (Google, 2017)[3].

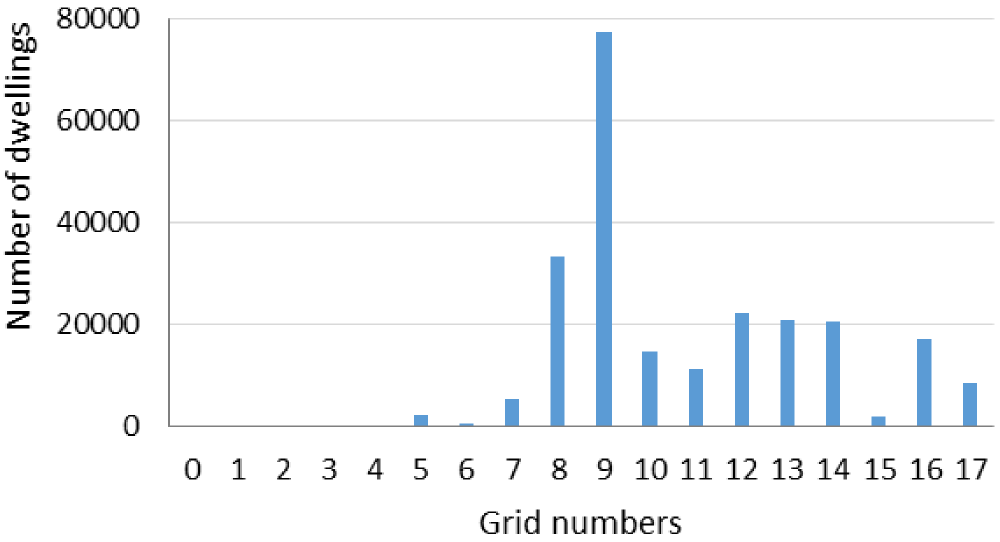


Figure 5-2. Number of dwellings in each UKCP09 grid square

[3] The underlying map of Sheffield was captured from the interactive map of UKCP09. The user interface of which links to Google Maps.

5.2.2. Building information and local shading measurements

In order to assess the fraction of overheated dwellings across the city, the number of dwellings and their form in each grid square was found. Residential areas were derived from Google Maps ® while the existing housing density was found in the report by URBED (URBED, 2015) obtained from Sheffield City Council. The number of dwellings is shown in Figure 5-2, note the significant difference in the number of dwellings between west (i.e. grid numbers 1 to 7) and east (i.e. grid numbers 8 to 17).

In order to gather the required detailed building information the survey tool of (Ramallo-González, 2015) was used. This tool utilises Google Street View® with Google Maps® so is applicable worldwide. The tool can be used to obtain window sizes and type (i.e. single or double), frame ratio and opening types (awning, casement, slider, hopper etc.), building type, orientation, local shading (i.e. angle of visible sky (Littlefair, 2001)) and (with human input) wall types (i.e. solid or cavity wall (EST, 2016)).

It would be infeasible to use the survey tool to garner the information needed to accurately model each of the 237,000 dwellings in the study area, so a random sample of buildings was selected in each grid square. The sample size used is shown in Table 5-1; note there are only a few rural houses in grid squares numbers 1 to 4 which are located within the National Park (see Figure 5-1 and Figure 5-2); in these cases all houses were assessed. The sample size S was found using equation 5-1 (NEA, 1960):

$$\mathrm{S} = \frac{X^2 \cdot n \cdot p \cdot (1-p)}{ME^2 \cdot (n-1) + X^2 \cdot p \cdot (1-p)} \tag{5-1}$$

where X^2 is found in a chi-square table for 1 degree of freedom with a given confidence level, n is the population size, p is the population proportion (%) and ME is the desired margin of error (%). The value of p is 0.5 which makes the maximum S (The Research Advisors, 2006). Given a confidence level of 90% and an ME of 10%, S for n between 50,000 and 264,000,000 is 68 which has been used for grid numbers 5 to 17. Using the survey tool five common gross UK dwelling types, i.e. detached houses, semi-detached houses, mid-terrace houses, (top floor) flats and bungalows were identified within the 907 stochastic dwelling measurements. The sample size and the distribution of each dwelling type across the whole study area is shown in Table 5-1.

Table 5-1. Sample size and distribution of each dwelling type across the seventeen grid squares

Grid numbers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	In total
Sample size	4	2	10	7	68	68	68	68	68	68	68	68	68	68	68	68	68	907
Detached (%)	1	1	2	1	13	11	10	9	4	8	7	3	2	3	9	12	4	100
Semi-detached (%)	0	0	1	0	6	9	7	8	5	8	6	9	7	9	7	8	11	100
Terraced (%)	0	0	1	0	1	3	10	7	18	8	8	7	13	10	5	4	6	100
Flat (%)	0	0	0	0	10	2	0	7	14	5	5	20	17	8	3	5	3	100
Bungalow (%)	1	0	0	6	13	8	6	6	2	7	14	2	3	3	16	6	6	100

5.2.3. Thermal modelling

Thermal models of the dwellings found, were created using DesignBuilder v4.2 with additional details from BEPAC Technical Note (Allen and Pinney, 1990). These building geometries were augmented with the surrounding obstructions to represent local shading, to create thermal models of 907 distinct dwellings in realistic settings. Since only the main façade of a dwelling is available from the survey tool in many cases, the windows on the other façades were predicted from the fenestration ratio of the measured values compared the ones recommended by the BEPAC Technical Note. Window opening types and glazing type were assumed to be consistent between the front and the rear of the dwelling. The images from the survey tool served to identify wall types i.e. solid or cavity wall but not wall insulation, which was estimated using the English Housing Survey Headline Report 2014-15: i.e. that 69% of the cavity walls were insulated while only 9% of the solid walls were insulated (DCLG, 2016). The three predominant constructions used in the thermal modelling were: (1) solid walls with single glazing and wooden frame windows, (2) uninsulated cavity walls with single glazing and wooden frame windows, and (3) insulated cavity walls with double glazing and uPVC frame windows. Details of constructions and derived thermal properties are presented in appendix A (also can be found in the online supplementary material (Liu, 2017)). Living rooms were assumed to be occupied between 9 a.m. and 10 p.m., while bedrooms were occupied between 11 p.m. and 8 a.m., based on the national overheating risk survey (Beizaee *et al.*, 2013). The number of occupants was assumed to be the number of bedrooms plus one assuming that two people occupy the main bedroom, with a single occupant for all other bedrooms (Building Regulation 2010). UK dwellings are typically not air conditioned, utilising natural ventilation for cooling during hot weather. Window opening was triggered in the models when (1) the internal temperature (T_{in}) > 24°C and (2) T_{in} > the external temperature (T_{ex}) and (3) only during occupied hours. In the simulations the aerodynamic opening area of the windows has been set to 20% of the total openable area. Internal gains from people, equipment, lighting, etc. were assumed to be 3.9 W/m^2 and 3.58 W/m^2 for living rooms and the main bedrooms respectively (Richardson and Thomson, 2010).

5.2.4. Overheating risk assessment

The indoor thermal environment was assessed over the summer period from April to September using four metrics: (i) mean operative temperature, (ii) average daily maximum operative temperature, (iii) percentage of occupied hours above the threshold operative temperatures i.e. 28°C for the living room and 26°C for the bedroom, and which should be no more than 1% over the year (CIBSE, 2006a), and (iv) Weighted Cooling Degree Hours (WCDH) (CIBSE, 2014). Hours of overheating was used to identify the number of overheated dwellings while WCDH was used to measure the severity of overheating.

In addition to the above metrics, the risk to human life from overheating was also estimated based on the methodology proposed by Armstrong *et al.* (2011). Armstrong *et al.* (2011) found that excess summer deaths are strongly associated with the summertime 2-day mean external temperature (T_{2-day}^{mean}), with the relative risk of death increasing linearly above a threshold temperature. This threshold temperature was shown to be coincident with the 93rd percentile of T_{2-day}^{mean} for all regions investigated (Armstrong *et al.*, 2011). Thus the heat-related mortality (M) for a summer was calculated from the relative risk (RR) given by:

$$M = D_{summer}^{all-cause} \cdot (RR - 1) \tag{5-2}$$

with

$$D_{summer}^{all-cause} = \frac{d}{365} \cdot D_{year}^{all-cause} \tag{5-3}$$

and

$$RR = \alpha \cdot T_{2-day}^{mean} + \beta, \tag{5-4}$$

where $D_{summer}^{all-cause}$ is the deaths over the summer from all causes, $D_{year}^{all-cause}$ the deaths in one year from all causes, and d is the number of days when the T_{2-day}^{mean} is above the threshold temperature identified for heat-related mortality. RR is the relative risk, a linear relationship between external temperature and mortality; α is the heat-mortality slope in % per degree above the mortality threshold temperature. The external mortality threshold temperature for Sheffield has been shown to be 22.2°C with α equal to 1.7% (Armstrong *et al.*, 2011). β can be calculated when RR equals

1 and T_{2-day}^{mean} is equal to the mortality threshold temperature. For this paper, which considers the spatial overheating risk across a city and for different dwelling types, external temperature is not an ideal indicator of the relative risk of mortality, instead it is preferable to use an internal mean temperature. To calculate the mortality rates for this study we have assumed that the mortality threshold temperature will occur at the 93rd percentile of internal 2-day mean temperatures, as it does externally. For each of the 17 grid squares the 100 HSY files were ranked in order to obtain the 93rd percentile of external T_{2-day}^{mean}. By choosing like percentiles from each grid square (e.g. median HSY from grids 1, 2, 3, etc.) the equivalent internal mortality threshold temperature was identified for each of the 907 dwellings (using living room temperatures for daytime and bedroom temperatures for night-time) and the average was taken to produce a citywide internal mortality threshold. In this way 100 citywide mortality thresholds were created to allow the probabilistic assessment of the relative risk. Population and $D_{year}^{all-cause}$ information was extracted at Middle Layer Super Output Area (MSOA) data from the UK Office for National Statistics (ONS) (ONS, 2011b). However, MSOAs do not match up with the UKCP09 grids, hence RR for each MSOA was adjusted based upon the proportion of the MSOA within each UKCP09 grid square.

5.3. Results and discussion

5.3.1. Variability in the external environment

External mean (T^{ex}_{mean}) and average daily maximum temperature (T^{ex}_{max}) over the summer (April to September) were calculated for the 100 pHSYs (i.e. 1st to 100th percentile HSYs) for each grid square for the 2020s (which is intended to represent the current climate). The variation of T^{ex}_{mean} and T^{ex}_{max} across the city is shown in Figure 5-3. The median values (red line in the box plot) of T^{ex}_{mean} and T^{ex}_{max} were found to have a variance of 0.40 and 0.61 respectively. The largest differences for the median values of T^{ex}_{mean} and T^{ex}_{max} among the seventeen grids were 2.8°C and 3.1°C respectively. In addition, median T^{ex}_{mean} and T^{ex}_{max} in the western region (grid numbers 1 to 7) were 1.6°C and 1.9°C lower than the eastern region (grid numbers 8 to 17). Given the difference in temperature between adjacent grid squares is up to twice as much as that indicated by the surface temperature lapse rate, it is clear that lapse rate alone is not a good way to account for variations in temperature across the landscape when considering overheating. Regarding the variation from 100 pHSYs within each grid, the variances of T^{ex}_{mean} and T^{ex}_{max} were approximately 0.4 and 0.6°C^2 respectively, which are consistent for all of the seventeen grids.

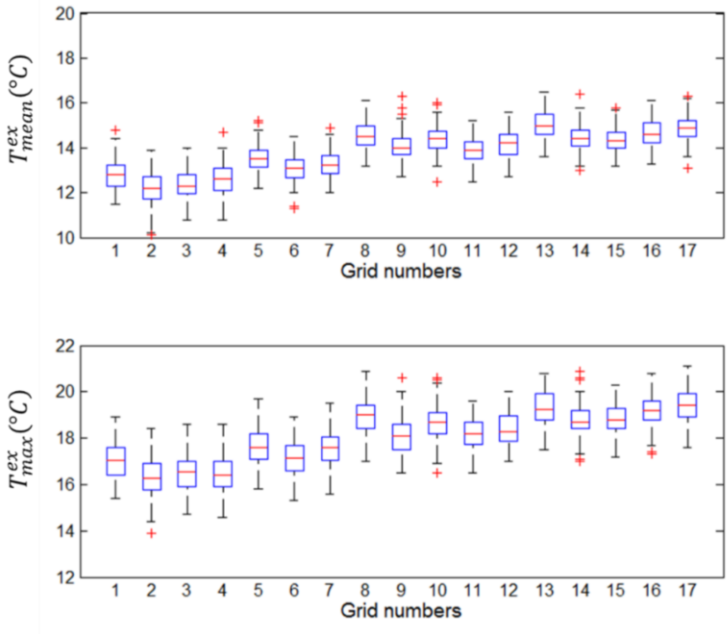


Figure 5-3. External mean and average daily maximum temperatures over the summer period (April to September) for the 2020s.

5.3.2. Variability in the indoor thermal environment

Across the 17 grid squares, 907 dwellings were simulated using a high performance computing environment for 100 pHSYs, resulting in 90,700 simulations for each time period. As might be expected from the external temperature, the indoor environment in the eastern region was warmer than the western region (Figure 5-4). On average, the difference in T_{max}^{in} between the two regions was 1.8°C for the living rooms and 1.4°C for the main bedrooms. The variability in T_{max}^{in} between the 17 grid squares however was up to 3.9°C for the living rooms and up to 3.1°C for the main bedrooms. The variances of T_{max}^{in} across the 17 grid squares were 1.0 and 0.75°C^2 for the living rooms and the main bedrooms respectively, i.e. higher than the variance of T_{max}^{ex} shown in Figure 5-3. For each grid square, there was greater variation in T_{mean}^{in} and T_{max}^{in} than in T_{mean}^{ex} and T_{max}^{ex}, suggesting variability does arise from the way the spectrum of dwelling types and their context varies over the study area, in addition to the weather.

Figure 5-5 shows a comparison between median internal operative temperatures (i.e. T_{mean}^{in} and T_{max}^{in}) for the 2020s and 2050s. For both the living room and the main bedroom the differences in median internal temperatures (ΔT, see secondary y-axis in Figure 5-5) between the 2020s and 2050s was < 1°C over the summer for all seventeen grid squares. In addition, the distribution for the 2050s was very similar to that for the 2020s indicating that the distribution in overheating risk is unlikely to change substantially due to a changing climate.

In summary, due to a combination of their architecture, their context and their location the dwellings in the eastern region are at a higher overheating risk than those in the western region and will remain so in future. This suggests that any policies should preferentially consider the population living in this area. In addition, the largest absolute difference of internal temperature (3.9°C) between grid squares is approximately twice as much as the difference (1.6°C) in external temperature from a consideration of surface temperature lapse rate alone. Thus it is clear any variations in external temperature caused by the lapse rate across a region should not be seen as indicative of internal temperature differences across the region. This conclusion, which suggests that overheating assessments must take into account of how the architecture and shading context changes across a region, supports previous work (Coley and Kershaw, 2010). This showed that the increase in internal temperature due to a changing climate was very much dependent on built form. With some buildings increasing in mean and maximum temperature faster than any changes in external temperature, and some less rapidly than the external perturbation.

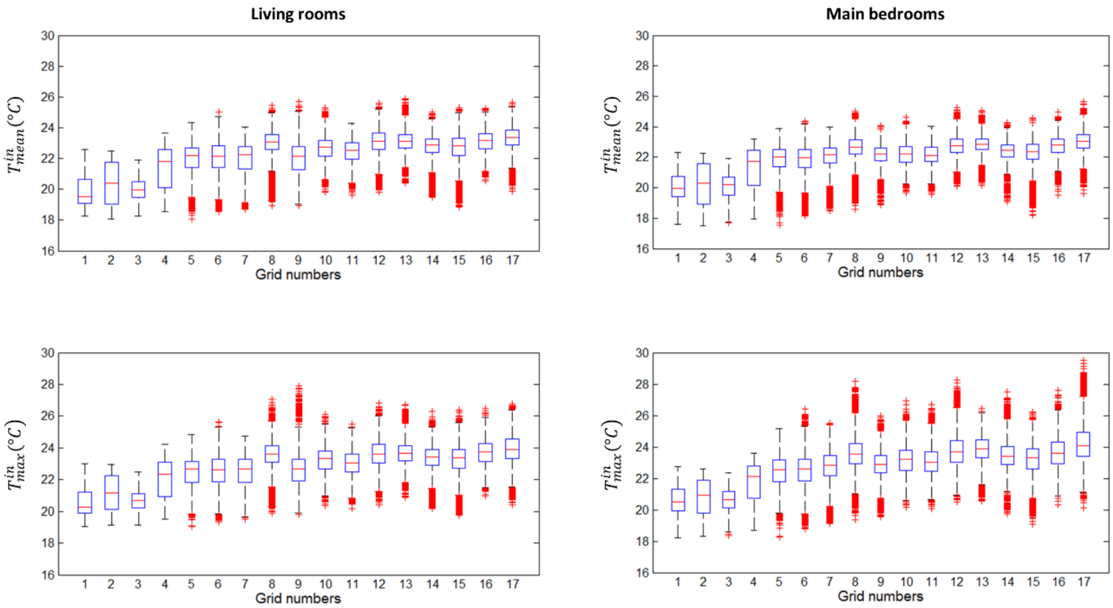


Figure 5-4. Internal mean and average maximum operative temperatures during the summer (April to September) in the 2020s.

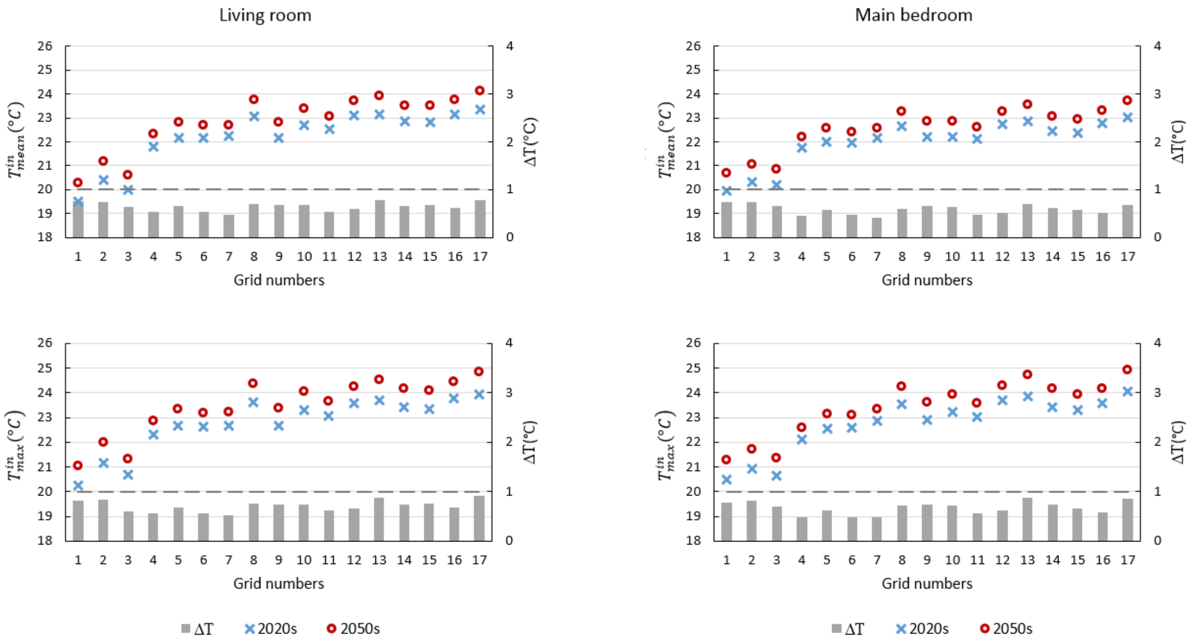


Figure 5-5. Variation in the median T^{in}_{mean} and T^{in}_{max} across the city in the 2020s and in 2050s. ΔT shows the increase in T^{in}_{mean} (or T^{in}_{max}) by the 2050s compared to the 2020s.

As mentioned above, 907 thermal models of dwellings were simulated with 100 pHSYs, resulting in 100 probabilistic projections of overheating risk per dwelling, or 90,700 predictions in total. The median (50^{th} percentile) projection of overheating for each of the 907 dwellings, sorted by type for all four overheating metrics considered, is shown in Figure 5-6. The method used, which is based on real survey data and shading, allows for a much more accurate consideration of which architectural forms are more at risk of overheating than work based on archetypes. It accounts for example for the observation (confirmed by the survey tool) that the lower floors of terrace housing in the urban environment is more likely to be shaded by other properties than detached homes in the suburbs. Comparisons between dwelling types indicate that, living rooms in the semi-detached houses, flats and bungalows, and bedrooms in the semi-detached and terraced houses are likely to be at a higher risk of overheating. Overall, detached houses were the coolest dwelling type which is consistent with results from previous work (Beizaee *et al.*, 2013). Top floor flats showed the highest overheating risk for living rooms (see Figure 5-6); this also agrees with the same reference. By contrast, for terraced houses overheating risk was lower in the living rooms compared to the bedrooms. Table 5-2 shows the percentage of overheated living rooms and bedrooms for each dwelling type for both 2020s and the 2050s. The number of overheated living rooms is projected to double by the 2050s compared to the 2020s, while the number of the overheated bedrooms is projected to increase dramatically by the 2050s.

Table 5-2. Percentage of overheating dwellings, shown by dwelling type, data shown at the 50^{th} percentile (Median). N is the number of samples.

Periods	Rooms	Detached (N=185)	Semi-detached (N=400)	Terraced (N=177)	Flat (N=59)	Bungalow (N=86)
2020s	Living room	18.4%	31.0%	18.1%	44.1%	33.7%
	Bedroom	0.0%	7.5%	44.6%	1.7%	8.1%
2050s	Living room	45.9%	69.8%	50.8%	88.1%	70.9%
	Bedroom	5.4%	42.3%	97.7%	42.4%	46.5%

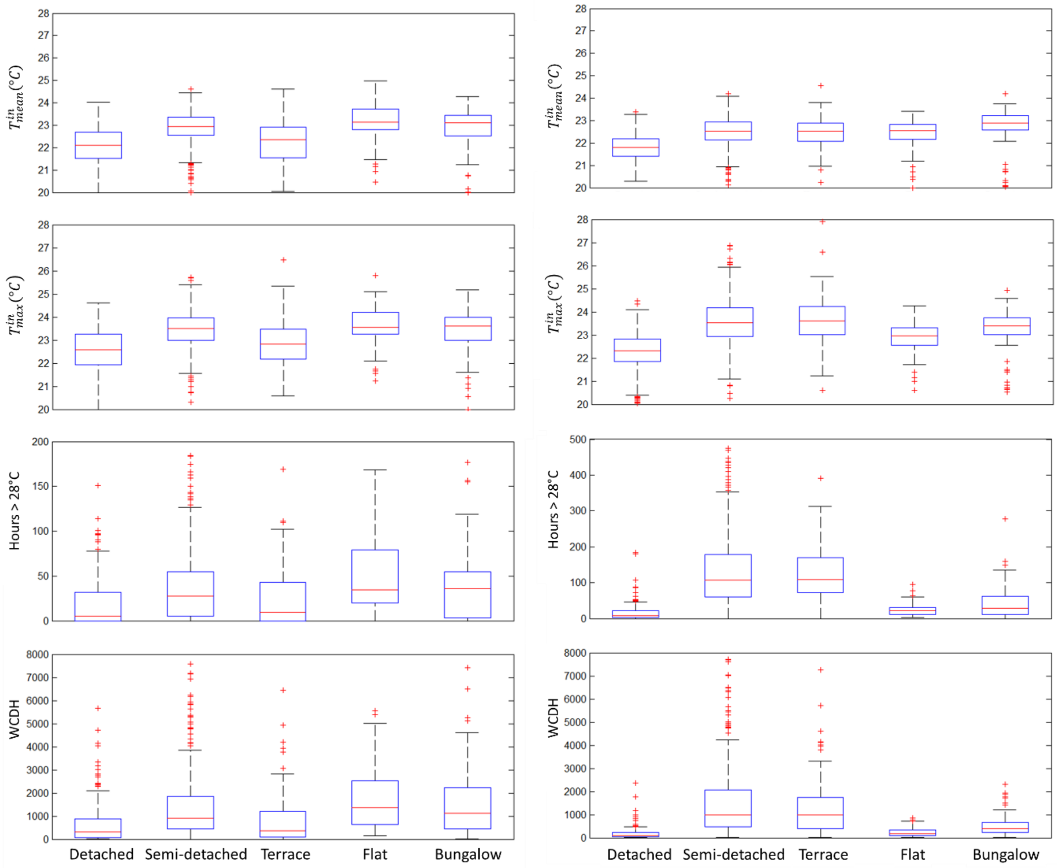


Figure 5-6. Variability in overheating for the different metrics for different dwelling types (living rooms on left; main bedrooms on right).

5.3.3. Maps of overheating risk

Maps of overheating were created, detailing both the number of overheating dwellings (based on hours of overheating) and the severity of overheating (based on WCDH) (Figure 5-7). The size of a circle illustrates the number of overheated dwellings while the colour displays the severity of the overheating risk. The number of the overheated dwellings in each grid square was estimated from the percentage of overheated samples and the actual number of dwellings shown in Figure 5-2. WCDH is found to increase by 50% for the living rooms and 19% for the main bedrooms for the 2050s compared to the 2020s.

There is a significant difference in the risk and severity of overheating between grid squares and between the eastern and western regions. This can be attributed not only to the higher external temperatures on the east side of the city but also the increased number of dwellings. On the west side of the city, only 3% of living rooms overheated in the 2020s rising to 16% by the 2050s (median estimate). While on the east side of the city overheating of living rooms was 34% and 74% for the 2020s and 2050s respectively. With respect to bedrooms, the east of the city showed approximately three times the risk than the west. The maps illustrate the high variability of both the overheating risk to dwellings and the severity of the overheating across the city.

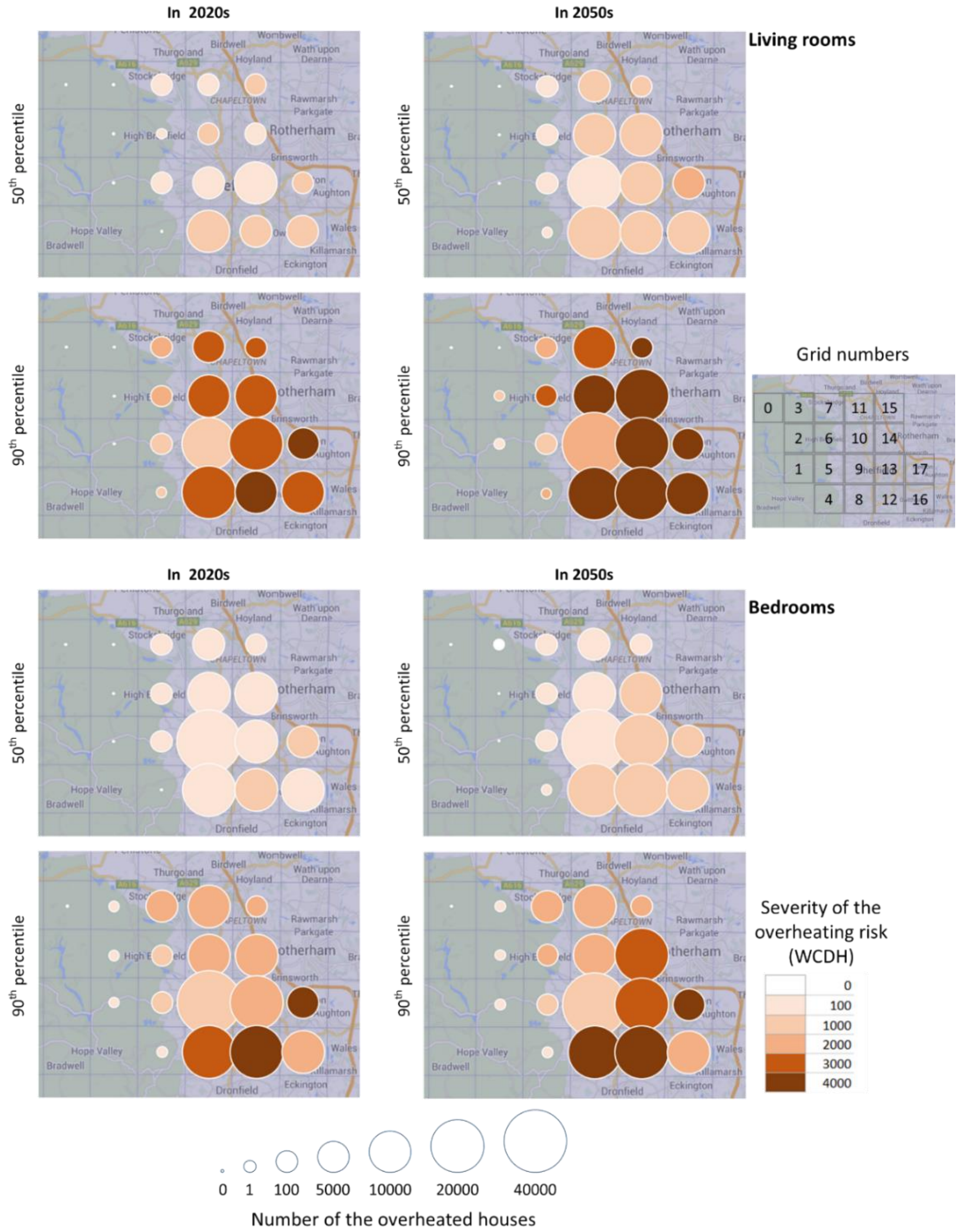


Figure 5-7. Overheating risk maps for the study area for the 2020s and 2050s. The size of the circle represents the number of overheating dwellings exceeding 1% of annual occupied hours above a set temperature. The colour scale represents the severity of the overheating risk measured by the number of WCDH.

5.3.4. Spatial variability of overheating risk

We have seen that the risk and severity of overheating varies with both location and architecture/context. This section examines which has the greater impact.

Within each pane, variability in T_{mean}^{in}, T_{max}^{in}, hours of overheating and WCDH are shown in Figure 5-8 and Figure 5-9. Variability in the weather between different grid squares is shown on the left; while variability between different samples of a single dwelling type is shown on the right.

In order to assess the variations in the overheating risk due to the spatial variability in the localised weather, two thermal models for each dwelling type were simulated with all of the weather files from across the city. The two thermal models were selected as follows: all the buildings within each dwelling type were ranked in order of overheating risk in the living room and the median model was selected; the other one was selected in the same way but based on the overheating risk in the main bedroom. Each model was simulated using 100 pHSYs for each grid square and the median result for each overheating metric was used to create the left-hand box plots. To assess the variability of different dwellings, all the thermal models within the same dwelling type were simulated with 100 pHSYs for the same location (weather data for grid square 9 was used, as this has the highest housing density and is in the middle of the city). For each dwelling model the median value of each overheating metric was used to create the right-hand boxplot. In summary, we are moving one building (the median one) of each basic type around the city and studying the variation in overheating found; and also placing all the buildings of the same type into one grid square to also look at the variation found. This allows a comparison in the variance due to weather to be compared to the difference caused by architecture and context.

As shown in Figure 5-8 and Figure 5-9, the interquartile ranges (IQR) of $T_{mean}^{in}$and T_{max}^{in} (left-hand box plots) for all dwelling types are similar. We can also see from Figure 5-8 and Figure 5-9 that the IQR of T_{mean}^{in} and T_{max}^{in} for inter-dwelling type variability (right-hand box plots) is roughly double the IQR variability (left-hand box plots) due to localised weather variability. This increased inter-dwelling type variability is carried over into the plots for hours of overheating and WCDH. The IQR of the hours of overheating and WCDH is shown to be up to 56 and 2150 for the living rooms and 101 and 1591 for the main bedrooms. In addition, the inter-dwelling type plots have a significantly greater range, highlighting the importance of the local setting on both overheating risk and severity. Such variability implies that it may be more appropriate to present a likely range of overheating risk based on a number of samples for a dwelling type rather than a single archetype model which may well show significantly biased results. The spatial variability in the localised weather also has a significant impact on the likely range of overheating risk, albeit to a lesser extent than the local context. The IQR of the hours of overheating and WCDH due to the variability in the weather, were in excess of 20 hours and 400 for the living rooms for all dwelling types and over 60 hours and 800 for the main bedrooms of semi-detached and terraced houses. The spatial variability in the weather therefore should be taken into consideration when completing risk assessments, though its influence was not as great as the variability in the dwellings.

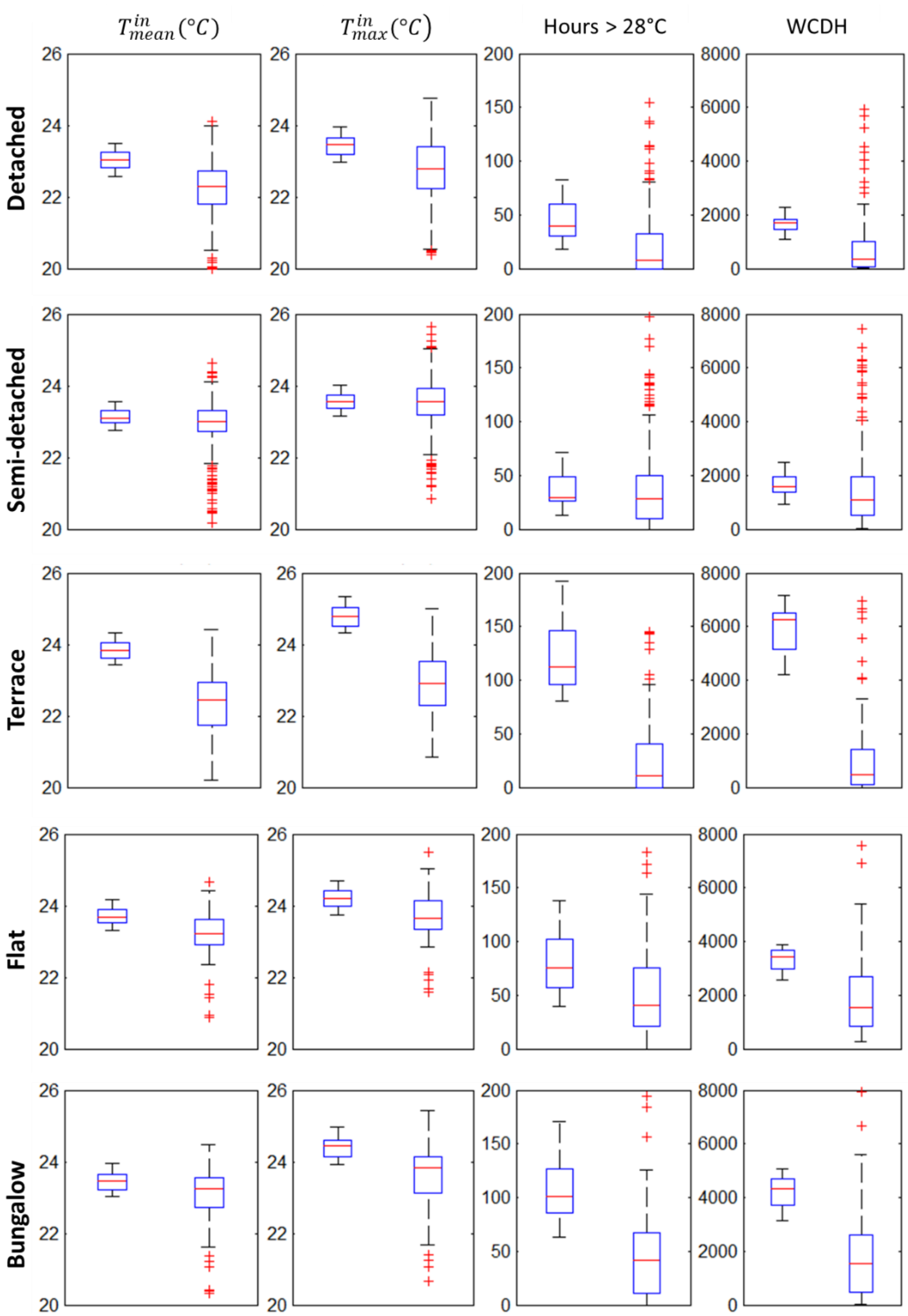


Figure 5-8. Comparison between the influence of variability of localised weather and dwellings for different overheating metrics within living rooms. The left-hand boxplot in each cell shows the variation caused by the spatial variability in the weather across the seventeen grids squares while the right-hand boxplot shows the variation given by all the samples within each dwelling type, but for a single grid square—i.e. the variability due to the architecture and context.

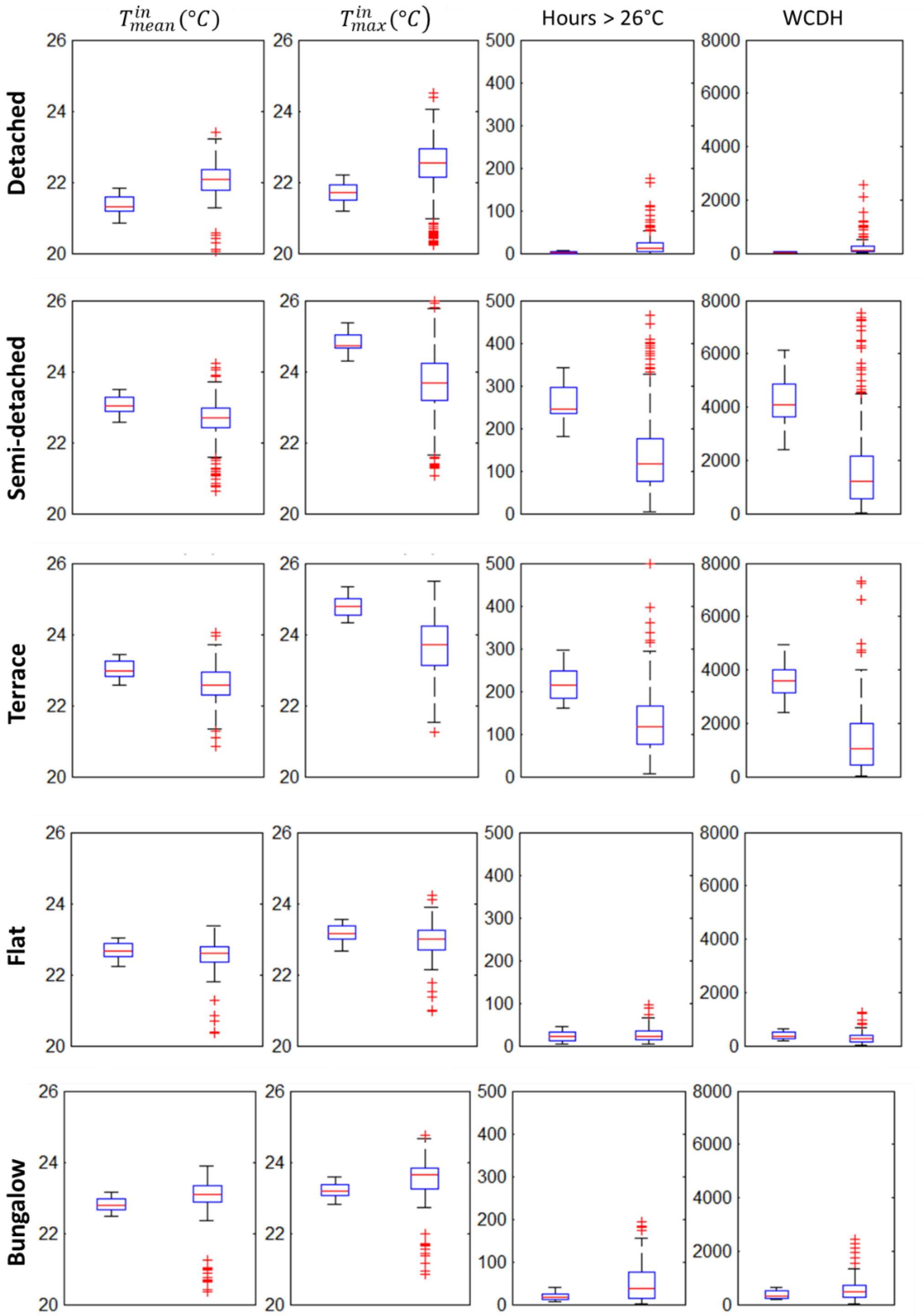


Figure 5-9. Comparison between the influence of variability of localised weather and dwellings for different overheating metrics within main bedrooms. The left-hand boxplot in each cell shows the variation caused by the spatial variability in the weather across the seventeen grids squares while the right-hand boxplot shows the variation given by all the samples within each dwelling type, but for a single grid square—i.e. the variability due to the architecture and context.

5.3.5. Validation and heat-related mortality at a sub-city level

As stated in the methodology, the mortality M is determined from the linear relationship between relative risk and the internal 2-day mean temperature (T_{2-day}^{mean}) above a citywide mortality threshold temperature. From the latest population and $D_{year}^{all-cause}$ data available at the MSOA (ward) level (ONS, 2011b), the heat-related mortality rates (M) in deaths/million over the summer (April to September) were estimated.

It is currently unclear at what rate people may adapt to higher temperatures as the climate changes. If people do not adapt quickly the mortality threshold temperature for the 2050s will be similar to the 2020s. Therefore, two maps have been produced for the 2050s, one where the 2020s mortality threshold has been used to calculate M and one where a new threshold temperature has been calculated to represent full adaptation to a warmer climate. The citywide mortality thresholds were calculated as 24.4°C and 25.9°C for the 2020s and 25.4°C and 27.2°C for the 2050s at the 50th and 90th percentiles respectively. The 50th and 90th percentile projections of M for the 2020s are 7 and 12 per million per year respectively, increasing to 21 and 39 per million per year in the 2050s in the absence of any adaptation (using the 2020s mortality threshold). Thereby indicating that the heat-related mortality rate would triple in a 30-year period if people were unable to adapt to a warming climate.

By using pHSYs this work is predicated on warmer than average summers and hence overestimates risk during colder summers. However, the weather generator (Jones *et al.*, 2010) that lies behind the pHSYs is not designed to produce heat waves or other rare events with long return periods. The pHSY is designed to solve this difficulty of needing to ensure overheating risk is not underestimated by using only typical years, but recognising there being (as yet) no robust way of generating accurate heat waves with accurate return periods across a landscape. The approach was validated by considering data from the hot summer of 2006. During May to August in 2006 (which included a 4-day hot spell) M for London was estimated (based on the recorded temperatures) as 33.5 per million (14.2 per million during one 4-day spell) (Taylor *et al.*, 2015). So, with the 90th percentile projection for the 2050s, Sheffield would experience yearly heat-related mortality similar to that found for London during the hot summer in 2006.

The mortality rate shown at a ward level across the city of Sheffield shows similar spatial variation to the overheating displayed in Figure 5-7, with the eastern region showing significantly greater heat-related mortality rates than the western region. Also variation between regions is more pronounced in the 2050s compared to the 2020s. The variances for the 50th and 90th percentile M are 21 and 79 for the 2020s but 142 and 403 for the 2050s.

If people do adapt quickly to the warming climate (using the threshold temperatures of mortality for the 2050s), the 50th and 90th percentile projections of M for the 2050s are 6 and 16 per million which are quite similar to the M of the 2020s suggesting that the adverse impact of the warming climate on M could be offset by human thermal adaptation. Also the spatial variation does not change as the variances for the 50th and 90th percentile M are 18 and 80, i.e. similar to those of the 2020s. Figure 5-10 shows M at a ward level, for the 2020s and 2050s at the 50th and 90th percentiles for both levels of adaptation.

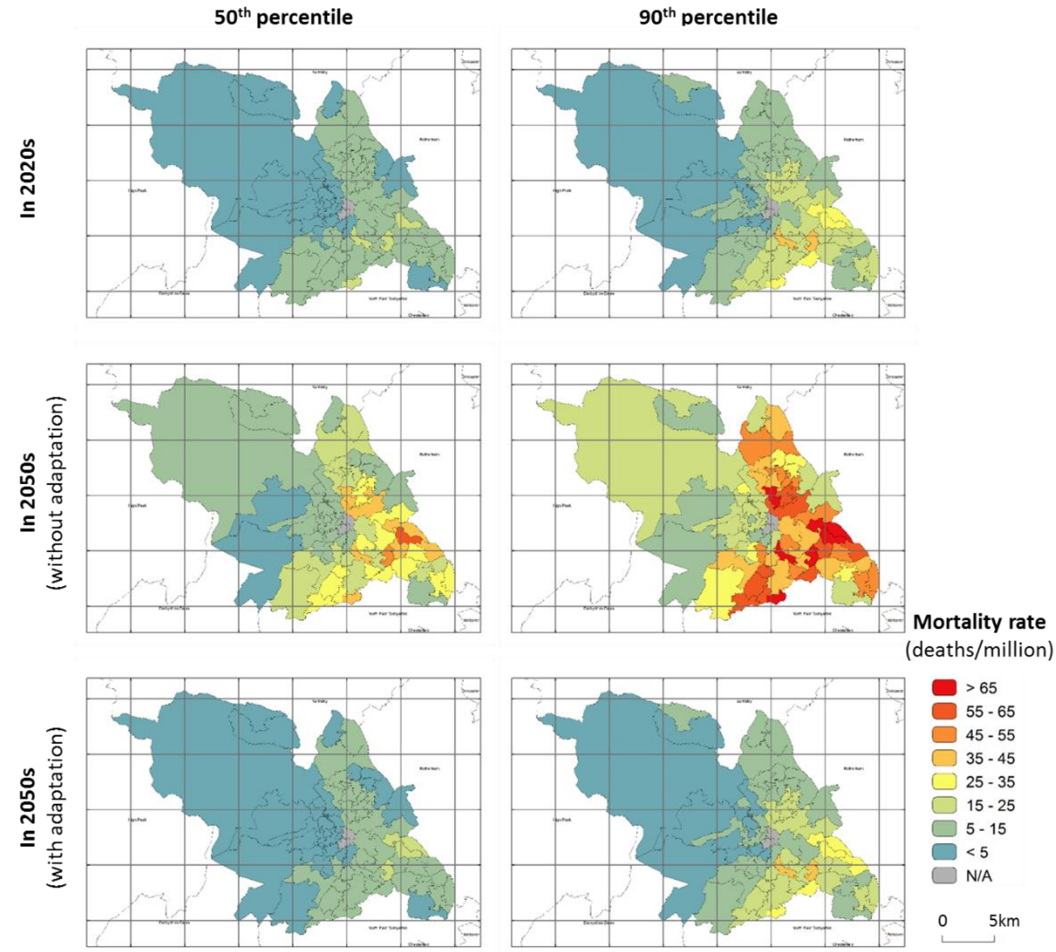


Figure 5-10. Heat-related mortality rates (deaths/million) for the 2020s and 2050s. The mortality rates with and without human adaptation to the warming climate are shown for the 2050s. Two MSOAs lack death data and are coloured grey. The 5km by 5km UKCP09 grid is overlaid for reference. The population of an MSOA on average is 7,200.

5.4. Conclusions

In this paper we have developed a new method for mapping the spatial variability of overheating and associated human mortality rates of a city, region or country and validated this against measured data for London. By applying the approach to a medium sized mid-latitude city and its surrounding countryside we have shown that spatial variability is material to the question of overheating assessment, and that much of this variability arises from the way building type varies across a region.

Rather than using a national stock model approach, which might not account for local architectural features, or shading from local street layouts, a robust stochastic approach was used. A remote survey tool (Ramallo-González, 2015) was used to gather the details of 907 buildings and their surroundings within seventeen 5km by 5km grid squares. The details included building type, building orientation, shading from the surrounding context, wall types, window types, glazing ratio, opening types and opening area. Each of these 907 dwellings were simulated using dynamic thermal modelling using standard occupancy levels and internal gains and probabilistic localised weather data for the 2020s and 2050s.

Examination of temperatures across the city show a strong correlation between external temperatures and topography. While, variation in T_{mean}^{in} and T_{max}^{in} across the city is more strongly correlated with the type of dwelling. In all cases the inter-dwelling type variability in overheating for all overheating metrics considered is greater than the variability due to weather. This implies that the details of local surroundings and local architecture are an important aspect when considering overheating risk.

Overheating maps have been created which show both the risk of overheating (based upon a number of hours criterion) and the severity of overheating (based upon WCDH). The maps show high spatial variations in both the risk and severity of overheating in dwellings across the city. The eastern side of the city showed overheating risk over three times that of the western side for the 2020s and 2050s. The maps indicate that the number of overheated dwellings and the severity of such overheating will increase substantially by the 2050s in the absence of any building adaptations. Such overheating maps will be a useful resource to identify areas of concern regarding the risk and severity of overheating in dwellings and for developing policy.

The impacts of location and vernacular form are also found to be important when considering heat related mortality, with some areas experiencing a 10-fold greater mortality rate than others.

It is clear from this work that it is critical to consider both the local weather and the local architecture (and its surroundings) when analysing overheating risk and future mortality rates. Doing so will also allow the identification of priority areas for adaptation of buildings, and priority populations, and thereby inform decision making about action plans.

6. Conclusion

The European heatwave in 2003 caused thousands of excess deaths due to thermal failures in buildings. The frequency and intensity of heat waves are very likely to increase, and the extremely hot summer in August 2003 will become the norm in foreseeable future due to a warming climate. Therefore, it is urgent to make buildings adapt to climate change to reduce overheating risk and avoid heat-related deaths. Thermal simulation with summer reference years such as the DSYs has been an important exercise to assess the risk of overheating. This study aimed to assess the risk of overheating and heat-related mortality at a high spatial resolution across a UK city under changing climates and to analyse the spatial variation driven by variability of vernacular forms and localised weather conditions. This research is highly important for the governments to identify the area of critical concern regarding population of overheated dwellings and heat-related mortality, and then prioritise the adaptation strategies accordingly. In order to achieve the research aim, innovative approaches have been proposed in this study to create appropriate and localised summer reference years as well as realistic thermal models in order to overcome the limitations of previous studies.

As discussed above, the existing DSY is not robust due to its simple selection method which was also used to produce the future pDSYs. Efforts have been made to overcome the shortcomings but none of them could provide robust summer reference years. This study proposed two approaches to the creation of new future summer reference years based on UKCP09 Weather Generator. One (pHSY-1) was created based on the WCDH in order to address the issue that DSY is not suitable for measuring the severity of overheating. The other (pHSY-2) was created based on PET which considers all the thermally related weather variables in order to address another main issue with DSY that it was selected based on a single weather variable (i.e. mean summer temperature) ignoring other thermally related weather variables, such as solar radiation, humidity and wind speed. Both the pHSY-1 and pHSY-2 for different future climate scenarios were produced for fourteen UK sites and compared with the existing future pDSYs and pTRYs based on different assessment metrics. A considerable limitation was that different assessment metrics would be very unlikely to deliver consistent results for both existing (pDSY) and new summer reference years (pHSY-1 and pDSY-2). An interesting finding of this study is that a single metric (e.g. hours above threshold temperature or WCDH) should be used if the risk of overheating is assessed with pHSY-1, which was created based on ascending order of a single weather variable, while a composite metric (e.g. hours above PET of 23°C or PMV 0.5) should be used if the thermal stress is evaluated with pHSY-2 which was created based on a thermal index, i.e. a measure of an integral effect of multiple weather variables. It has been justified that both pHSY-1 and pHSY-2 were more robust than the existing pDSY as they could consistently indicate a greater risk of overheating or thermal stress than the pTRY, i.e. the typical years. These findings have a profound implication for the further development of summer reference years for use in the assessment of overheating and thermal stress.

In addition, a few dwelling archetypes with little or no concern about surrounding shading effects have been used in previous research on the variation in overheating across a landscape due to the lack of such information at a large scale. For the first time, real dwellings and their local shading were remotely measured at a 5km by 5km resolution for a UK city, i.e. Sheffield using a remote survey tool. Approximately, a thousand realistic thermal models were created based on the measurement that included dwelling types, building orientations, wall types, glazing types and ratios, opening types and ratios, and surrounding obstruction. These elements are key to the indoor thermal comfort analysis. Current and future pHSYs were also created at a 5km by 5km horizontal resolution in order to account for the variability of local weather across the landscape of the city. The following outcomes of this study are convincing due to such a great number of realistic thermal models combined with localised and robust future pHSYs. The spatial variation in overheating due to the variability in the vernacular form, context and localised weather were investigated for the city with great topographic and housing density variation. Maps of overheating and heat-related mortality under current condition and in a future changing climate for the city have been presented. It was found that the impact of changing climates on the risk of overheating and its associated mortality was significant. Without building adaptations, there would be a significant increase in the risk of overheating in the 2050s compared to the current climate, which is in line with previous findings. Furthermore, the heat-related mortality rate will be tripling in next 30 years without human thermal adaptations. However, the increases due to rising land surface temperature could be significantly offset by human thermal adaptations. Though such passive adaptations could not guarantee safe and comfortable indoor environment against a warming climate, they are beneficial to reducing the cooling energy and mitigating global warming. Another important finding of this study was that the spatial variation in the severity of overheating driven by the variability of the local dwellings, local shading and localised weather was greater than previously thought. Moreover, variability in the inter-dwelling types had a greater influence on overheating compared to the variability in localised weather. A rather remarkable outcome from this study was the high resolution overheating and heat-related maps which allow policy makers to identify the area of critical concern regarding the population of overheated houses, severity of overheating and heat-related mortality, and then make cost-effective adaptation strategies to protect people against the warming climate.

The limitation of this study is that a few reasonable assumptions had to be made about the unavailable information such as the floor, loft and roof insulation, occupancy schedules and internal gains when creating thermal models of real dwellings. Future research could usefully explore more construction types, different occupancy schedules and internal gains. Another limitation of this research is that the age of the population was not considered when estimating the heat-related mortality rate for the 2020s and the 2050s. The actual heat-related mortality rates in the 2050s might be higher compared to the estimates in this work due to the aging population. Notwithstanding these limitations, this study offers valuable insights into the effect of human thermal adaptation to the warming climate and influence of variability in vernacular forms and localised weather on spatial variation in the risk of overheating and heat-related mortality.

As an expansion of this study, it would be interesting to assess the risk of overheating under a changing climate for other countries. This study proposed future pHSY-1 and pHSY-2 which were created based on the synthetic future weather data set from UKCP09 WG which incorporates probabilistic UK climate change projections. Though UKCP09 WG is able to provide current and future weather data at a high spatial resolution, it cannot generate such data beyond the UK. However, it is possible to generate future weather data for other countries by morphing the historical observed weather data using the probabilistic climate change projections from regional and global climate models. Therefore, the future pHSY-1 and pHSY-2 could be produced for other countries to assess the overheating risk under a warming climate worldwide. In addition, future research should be carried out to test the effectiveness of various design alternatives in order to provide sustainable and appropriate building adaptations against future changing climate. A further study could test the resilience of the built environment to more extreme weather event such as heatwave. Future research should, therefore, concentrate on the development of future event years that include heatwave, i.e. consecutive days of high external temperatures to investigate the risk of overheating and heat-related mortality in a more holistic manner.

References

A Human Health Perspective On Climate Change - A Report Outlining the Research Needs on the Human Health Effects of Climate Change [Online]. Environmental Health Perspectives and the National Institute of Environmental Health Sciences Available from: http://www.niehs.nih.gov/health/materials/a_human_health_perspective_on_climate_change_full_report_508.pdf [Accessed 16th May 2016].

Allen, E. & Pinney, A., 1990. *Standard dwellings for modelling: details of dimensions, construction and occupancy schedules.* Building Environmental Performance Analysis Club Watford, ND.

Armstrong, B.G., Chalabi, Z., Fenn, B., Hajat, S., Kovats, S., Milojevic, A. & Wilkinson, P., 2011. Association of mortality with high temperatures in a temperate climate: England and Wales. *Journal of Epidemiology and Community Health*, 65(4), pp. 340-345.

ASHRAE, 2005. *Fundamentals Handbook-Chapter 6 Psychrometrics.* Atlanta: American Society of Heating Refrigerating and Air-Conditioning Engineers.

ASHRAE, 2013. ANSI/ASHRAE Standard 55-2013 Thermal Environmental Conditions for Human Occupancy.

Augspach, P., 2014. Assessing Pedestrian Thermal Comfort within the Buenos Aires Climatic Context. *30th International PLEA Conference.* CEPT University, Ahmedabad.

BADC, Met Office Integrated Data Archive System Land and Marine Surface Stations data (1853-current) Internet: British Atmospheric Data Centre.

Beizaee, A., Lomas, K.J. & Firth, S.K., 2013. National survey of summertime temperatures and overheating risk in English homes. *Building and Environment*, 65(0), pp. 1-17.

Belcher, S.E., Hacker, J.N. & Powell, D.S., 2005. Constructing design weather data for future climates. *Building Services Engineering Research and Technology*, 26(1), pp. 49-61.

Big Ladder Software, 2017. *Auxiliary Programs: EnergyPlus Weather File (EPW) Data Dictionary* [Online]. Available from: http://bigladdersoftware.com/epx/docs/8-3/auxiliary-programs/energyplus-weather-file-epw-data-dictionary.html#field-data-source-and-uncertainty-flags [Accessed 18/04 2017].

Brager, G.S. & de Dear, R.J., 1998. Thermal adaptation in the built environment: a literature review. *Energy and Buildings*, 27(1), pp. 83-96.

BRE, 2005. *The Government's Standard Assessment Procedure for Energy Rating of Dwellings, RdSAP 2005 edition* [Online]. Warford, UK: Building Reseach Establishment Ltd. Available from: http://projects.bre.co.uk/sap2005/pdf/SAP2005.pdf [Accessed 04/10 2017].

BRE, 2012. The Government's Standard Assessment Procedure for Energy Rating of Dwellings. SAP 2009, Watford, UK: Building Research Establishment (BRE).

BSI, 2005. BS EN ISO 15927-4:2005: Hygrothermal performance of buildings-Calculation and persentation of climate data. *Part 4: Hourly data for assessing the annual energy use for heating and cooling*. London, UK.

BSI, 2006. *BS EN ISO 7730:2005 Ergonomics of the thermal environment. Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria.* London, UK: British Standards Institution.

BSI, 2007. BS EN 15251:2007: Indoor environmental input paramerters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics. London, UK: British Standards Institution.

Building Regulation 2010, *Approved Document F, Ventilation* [Online]. Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/468871/ADF_LOCKED.pdf [Accessed 20/11 2016].

Christidis, N., Jones, G.S. & Stott, P.A., 2015. Dramatically increasing chance of extremely hot summers since the 2003 European heatwave. *Nature Clim. Change*, 5(1), pp. 46-50.

CIBSE, 2006a. CIBSE Guide A: Environmental Design. London: The Chartered Institution of Building Services Engineers.

CIBSE, 2006b. CIBSE TM33: Tests for software accreditation and verification. London: Chartered Institution of Building Services Engineers.

CIBSE, 2013a. *CIBSE TM52: The limits of thermal comfort: avoiding overheating in European buildings.* London: The Chartered Institution of Building Services Engineers.

CIBSE, 2013b. *CIBSE Weather Data Sets* [Online]. Available from: http://www.cibse.org/knowledge/cibse-other-publications/cibse-weather-data-current,-future,-combined-dsys [Accessed 5th May 2014].

CIBSE, 2013c. Future CIBSE TRY/DSY Hourly Weather Data. London: The Chartered Institution of Building Services Engineers

CIBSE, 2014. CIBSE TM 49: Design Summer Years for London. London: The Chatered Institution of Building Services Engineers.

Clarke, J.A., 1977. *Environmental systems performance.* PhD thesis, University of Strathclyde.

Coles, S., 2013. *An Introduction to Statistical Modelling of Extreme Values.* London: Springer Science and Business Media.

Coley, D. & Kershaw, T., 2010. Changes in internal temperatures within the built environment as a response to a changing climate. *Building and Environment*, 45(1), pp. 89-93.

Coley, D., Kershaw, T. & Eames, M., 2012. A comparison of structural and behavioural adaptations to future proofing buildings against higher temperatures. *Building and Environment*, 55, pp. 159-166.

Crow, L., 1981. Development of hourly data for weather year for energy calculations (WYEC), including solar data, at 21 stations throughout the US. *Ashrae Transactions*, 87(1), pp. 896-900.

David Ferrari & Lee, T., 2008. BEYOND TMY: CLIMATE DATA FOR SPECIFIC APPLICATION. *In: Proceedings 3rd International Solar Energy Society Conference – Asia Pacific region (ISES-AP-08).* Sydney, Australia.

DCLG, 2011a. *English Housing Survey* [Online]. Department for Communities and Local Government, London, UK. Available from: https://www.gov.uk/government/collections/english-housing-survey [Accessed 04/10 2017].

DCLG, 2011b. *English Housing Survey: housing stock report 2009.* Department for Communities and Local Government, London, UK.

DCLG, 2015. *English Housing Survey TECHNICAL REPORT 2013-14.* Department for Communities and Local Government, London, UK.

DCLG, 2016. *English Housing Survey Headline Report 2014-15.* Department for Communities and Local Government, London, UK.

DCLG, 2017. *English Housing Survey Headline Report 2015-16.* Department for Communities and Local Government, London, UK.

de Dear, R.J., Brager, G.S., Reardon, J. & Nicol, F., 1998. Developing an adaptive model of thermal comfort and preference/discussion. *ASHRAE transactions*, 104, p. 145.

de Wilde, P. & Tian, W., 2009. Identification of key factors for uncertainty in the prediction of the thermal performance of an office building under climate change. *Building Simulation*, 2(3), pp. 157-174.

de Wilde, P. & Tian, W., 2010. Predicting the performance of an office under climate change: A study of metrics, sensitivity and zonal resolution. *Energy and Buildings*, 42(10), pp. 1674-1684.

de Wilde, P. & Tian, W., 2012. Management of thermal performance risks in buildings subject to climate change. *Building and Environment*, 55(0), pp. 167-177.

DECC, 2012. *National Energy Efficiency Data-Framework* [Online]. Department of Energy and Climate Change, UK. Available from: http://webarchive.nationalarchives.gov.uk/20130109092117/http://decc.gov.uk/en/content/cms/statistics/energy_stats/en_effic_stats/need/need.aspx [Accessed 05/06 2017].

DECC, 2013. *Energy Follow-Up Survey 2011*. Department of Energy and Climate Change, London, UK.

DECC & BRE, 2016. *Energy Follow Up Survey, 2011: Lookup File: Secure Access* [Online]. UK Data Service. Available from: https://discover.ukdataservice.ac.uk/catalogue/?sn=7883 [Accessed 05/06 2017].

Demanuele, C., Mavrogianni, A., Davies, M., Kolokotroni, M. & Rajapaksha, I., 2012. Using localised weather files to assess overheating in naturally ventilated offices within London's urban heat island. *Building Services Engineering Research and Technology*, 33(4), pp. 351-369.

Eames, M., 2016. An update of the UK's design summer years: Probabilistic design summer years for enhanced overheating risk analysis in building design. *Building Services Engineering Research and Technology*.

Eames, M., Kershaw, T. & Coley, D., 2010. The creation of wind speed and direction data for the use in probabilistic future weather files. *Building Services Engineering Research and Technology*, 32(2), pp. 143-158.

Eames, M., Kershaw, T. & Coley, D., 2011. On the creation of future probabilistic design weather years from UKCP09. *Building Services Engineering Research and Technology*, 32(2), pp. 127-142.

Eames, M., Kershaw, T. & Coley, D., 2012a. The appropriate spatial resolution of future weather files for building simulation. *J Build Perform Simu*, 5(6), pp. 347-358.

Eames, M., Kershaw, T.J. & Coley, D., 2012b. A comparison of future weather created from morphed observed weather and created by a weather generator. *Building and Environment*, 56, pp. 252-264.

Eames, M., Ramallo-Gonzalez, A. & Wood, M., 2015. An update of the UK's test reference year: The implications of a revised climate on building design. *Building Services Engineering Research and Technology*.

EDSL, 2015. *Tas Engineering* [Online]. Environmental Design Solutions Limited, UK. Available from: http://www.edsl.net/main/Software/Designer.aspx [Accessed 05/06 2017].

Ekström, M., Jones, P.D., Fowler, H.J., Lenderink, G., Buishand, T.A. & Conway, D., 2007. Regional climate model data used within the SWURVE project – 1: projected changes in seasonal patterns and estimation of PET. *Hydrol. Earth Syst. Sci.*, 11(3), pp. 1069-1083.

ESRU, 2017. *ESP-r* [Online]. Energy Simulation Research Unit, University of Strathclyde, Glasgow, Scotland, UK. Available from: http://www.esru.strath.ac.uk/Programs/ESP-r.htm [Accessed 03/05 2017].

EST, 2013. *Homes Energy Efficiency Database*. Energy Saving Trust, London, UK.

EST, 2016. *Cavity and solid walls* [Online]. Energy Saving Trust. Available from: http://www.energysavingtrust.org.uk/home-insulation/cavity-wall [Accessed 10/10 2016].

EST, 2017. *Housing data analysis: Home Analytics* [Online]. Energy Saving Trust, UK. Available from: http://www.energysavingtrust.org.uk/business/data-and-insight/housing-data-analysis [Accessed 02/06 2017].

Fanger, P.O., 1970. *Thermal comfort*. Copenhagen, Denmark: Danish Technical Press.

Fanger, P.O. & Toftum, J., 2002. Extension of the PMV model to non-air-conditioned buildings in warm climates. *Energy and Buildings*, 34(6), pp. 533-536.

Finkelstein, J.M. & Schafer, R.E., 1971. Improved goodness-of-fit tests. *Biometrika*, pp. 641-645.

Fouillet, A., Rey, G., Laurent, F., Pavillon, G., Bellec, S., Guihenneuc-Jouyaux, C., Clavel, J., Jougla, E. & Hémon, D., 2006. Excess mortality related to the August 2003 heat wave in France. *International Archives of Occupational and Environmental Health*, 80(1), pp. 16-24.

Frank, T., 2005. Climate change impacts on building heating and cooling energy demand in Switzerland. *Energy and Buildings*, 37(11), pp. 1175-1185.

Futcher, J.A., Kershaw, T. & Mills, G., 2013. Urban form and function as building performance parameters. *Build Environ*, 62, pp. 112-123.

Gagge, A.P., Fobelets, A. & Berglund, L., 1986. A standard predictive index of human response to the thermal environment. *ASHRAE Transactions*, 92, pp. 709–731.

Gaterell, M.R. & McEvoy, M.E., 2005. The impact of climate change uncertainties on the performance of energy efficiency measures applied to dwellings. *Energy and Buildings*, 37(9), pp. 982-995.

Glenn R McGregor, M.P., Tanja Wolf and & Gosling, S., 2007. *Science Report-The social impacts of heat waves*. Environment Agency, Rio House, Waterside Drive, Aztec West, Almondsbury, Bristol, BS32 4UD.

Google, 2017. *Map of Sheffield* [Online]. Google. Available from: The interactive map of UKCP09 User Interface http://ukclimateprojections-ui.metoffice.gov.uk/ui/req_bldr/location.php [Accessed 10 Feb 2017].

Gu, L., 2007. Airflow network modeling in EnergyPlus. *In: Proceedings 10th International Building Performance Simulation Association Conference (BS 2007).* Bejing, China.

Gul, M., Jenkins, D., Patidar, S., Banfill, P., Menzies, G. & Gibson, G., 2012. Tailoring a future overheating risk tool for existing building design practice in domestic and non-domestic sectors. *Building Services Engineering Research and Technology*, 33(1), pp. 105-117.

Gupta, R. & Gregg, M., 2012. Using UK climate change projections to adapt existing English homes for a warming climate. *Building and Environment*, 55(0), pp. 20-42.

Gupta, R. & Gregg, M., 2013. Preventing the overheating of English suburban homes in a warming climate. *Building Research & Information*, 41(3), pp. 281-300.

Hajat, S., Vardoulakis, S., Heaviside, C. & Eggen, B., 2014. Climate change effects on human health: projections of temperature-related mortality for the UK during the 2020s, 2050s and 2080s. *Journal of Epidemiology and Community Health*, 68(7), pp. 641-648.

Hall, I.J., Prairie, R., Anderson, H. & Boes, E., 1978. *Generation of a typical meteorological year*. Sandia Labs., Albuquerque, NM (USA).

Hirsch, J.J., 1981. *DOE-2 Building Energy Use and Cost Analysis Software*. Lawrence Berkeley National Laboratory, USA.

Hittle, D.C. & Lawrie, L., 1978. *The building loads analysis and system thermodynamics program (BLAST).* Army Construction Engineering Research Lab, Champaign, IL, USA.

Holden, J. & Rose, R., 2011. Temperature and surface lapse rate change: a study of the UK's longest upland instrumental record. *International Journal of Climatology,* 31(6), pp. 907-919.

Hoppe, P., 1999. The physiological equivalent temperature - a universal index for the biometeorological assessment of the thermal environment. *International journal of biometeorology,* 43(2), pp. 71-5.

Höppe, P., 1984. *Die Energiebilanz des Menschen: In: Münchener Universitätsschriften-Fachbereich Physik, Wissenschaftliche Mitteilungen Nr. 49.*, Universität München.

Höppe, P., 1993. Heat balance modelling. *Experientia* 49, pp. 741–746.

Höppe, P., 2002. Different aspects of assessing indoor and outdoor thermal comfort. *Energy and Buildings,* 34(6), pp. 661-665.

Houghton, F., 1923. Determining lines of equal comfort. *Transactions of Am. Soc. of Heat-Vent. Engineers,* 29, pp. 163-176.

Huang, Y.J., Su, F., Seo, D. & Krarti, M., 2014. Development of 3012 IWEC2 weather files for international locations (RP-1477). *ASHRAE Transactions,* 120, p. 340.

Humphreys, M.A., Nicol, J.F. & Raja, I.A., 2007. Field Studies of Indoor Thermal Comfort and the Progress of the Adaptive Approach. *Advances in Building Energy Research,* 1(1), pp. 55-88.

IES, 2014. *APlocate: Location and WEather User Guide* [Online]. Integrated Environmental Solutions Limited, UK. Available from: http://www.iesve.com/downloads/help/ve2014/Thermal/APLocate.pdf [Accessed 14/02 2017].

IPCC, 2000. *Emission Scenarios* [Online]. The Edinburgh Building Shaftesbury Road, Cambridge: Cambridge Universtiy Press,UK. Available from: http://www.ipcc.ch/ipccreports/sres/emission/index.php?idp=0 [Accessed 20th September 2015].

IPCC, 2007a. *Climate Change 2007: Synthesis Report.* Geneva, Switzerland.

IPCC, 2007b. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)].* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC, 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and*

P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jendritzky, G., Staiger, H., Bucher, K., Graetz, A. & Laschewski, G., Year. The perceived temperature: the method of the Deutscher Wetterdienst for the assessment of cold stress and heat load for the human body. In: Internet workshop on Windchill, 2000.

Jenkins, D.P., Patidar, S., Banfill, P.F.G. & Gibson, G.J., 2011. Probabilistic climate projections with dynamic building simulation: Predicting overheating in dwellings. *Energy and Buildings,* 43(7), pp. 1723-1731.

Jenkins, G.J., Murphy, J.M., Sexton, D.S., Lowe, J.A., Jones, P. & Kilsby, C.G., 2009. *UK Climate Projections: Briefing Report.* Met Office Hadley Centre, Exeter, UK.

Jenkins, K., Hall, J., Glenis, V., Kilsby, C., McCarthy, M., Goodess, C., Smith, D., Malleson, N. & Birkin, M., 2014. Probabilistic spatial risk assessment of heat impacts and adaptations for London. *Climatic Change,* 124(1), pp. 105-117.

Jentsch, M.F., 2012. *Climate change weather file generator (CCWeatherGen)* [Online]. Sustainable Energy Research Group, University of Southampton. Available from: http://www.energy.soton.ac.uk/ccworldweathergen/ [Accessed 20th Feb 2014].

Jentsch, M.F., Bahaj, A.S. & James, P.A.B., 2008. Climate change future proofing of buildings—Generation and assessment of building simulation weather files. *Energy and Buildings,* 40(12), pp. 2148-2168.

Jentsch, M.F., Eames, M.E. & Levermore, G.J., 2015. Generating near-extreme Summer Reference Years for building performance simulation. *Building Services Engineering Research and Technology,* 36, pp. 701-727.

Jentsch, M.F., Levermore, G.J., Parkinson, J.B. & Eames, M.E., 2013. Limitations of the CIBSE design summer year approach for delivering representative near-extreme summer weather conditions. *Building Services Engineering Research and Technology,* 35, pp. 155-169.

Ji, Y., Zhang, Y., Korolija, I. & Futcher, J., 2016. Design summer year weather – outdoor warmth ranking metrics and their numerical verification. *Building Services Engineering Research and Technology,* 37(6), pp. 639-663.

Johnson, H., Kovats, R.S., McGregor, G., Stedman, J., Gibbs, M. & Walton, H., 2005. The impact of the 2003 heat wave on daily mortality in England and Wales and the use of rapid weekly mortality estimates. *Euro surveillance : bulletin européen sur les maladies transmissibles = European communicable disease bulletin.,* 10(7), pp. 168-171.

Jones, P.D., Kilsby, C.G., Harpham, C., Glenis, V. & Burton, A., 2010. *UK Climate Projections science report: Projections of future daily climate for the UK from the Weather Generator.* University of Newcastle, UK

Jones, R., 2004. *Generating high resolution climate change scenarios using PRECIS.*: Met office.

K.J.Lomas & T.Kane, 2013. Summertime temperatures and thermal comfort in UK homes. *Building Research & Information,* 41(3, 2013).

Kershaw, T., Eames, M. & Coley, D., 2010. Comparison of multi-year and reference year building simulations. *Building Services Engineering Research and Technology,* 31(4), pp. 357-369.

Kershaw, T., Eames, M. & Coley, D., 2011. Assessing the risk of climate change for buildings: A comparison between multi-year and probabilistic reference year simulations. *Building and Environment,* 46(6), pp. 1303-1308.

Kilsby, C.G., Jones, P.D., Burton, A., Ford, A.C., Fowler, H.J., Harpham, C., James, P., Smith, A. & Wilby, R.L., 2007. A daily weather generator for use in climate change studies. *Environmental Modelling & Software,* 22(12), pp. 1705-1719.

Kolokotroni, M., Zhang, Y. & Giridharan, R., 2009. Heating and cooling degree day prediction within the London urban heat island area. *Building Services Engineering Research and Technology,* 30(3), pp. 183-202.

Kusuda, T.A.P.R.U.S.O.o.C.D., 1965. *Earth temperature and thermal diffusivity at selected stations in the United States.* [Washington, D.C.]: National Bureau of Standards.

Larsen, J., 2006a. *Setting the Record Straight: More than 52,000 Europeans Died from Heat in Summer 2003* [Online]. Earth Policy Institute. [Accessed 2 July 2014].

Larsen, J., 2006b. Setting the record straight: More than 52,000 Europeans died from heat in summer 2003. *Washington, DC: Earth Policy Institute*.

Lawrie, L.K., 2003. *EnergyPlus Weather Converter, Subroutine for ground temperature calculation: CalcGroundTemps.f90, Fortran code*

Lee, S.E. & Levermore, G.J., 2013. Simulating urban heat island effects with climate change on a Manchester house. *Building Services Engineering Research and Technology,* 34(2), pp. 203-221.

Levermore, G.J. & Parkinson, J.B., 2006. Analyses and algorithms for new Test Reference Years and Design Summer Years for the UK. *Building Service Engineering Research and Technology,* 27(4), pp. 311-325.

Liddament, M., 1986. Air Infiltration Calculation Techniques-an Applications Guide," Air Infiltration and Ventilation Centre, Bracknell, UK.

Lin, T.-P. & Matzarakis, A., 2008. Tourism climate and thermal comfort in Sun Moon Lake, Taiwan. *International journal of biometeorology,* 52(4), pp. 281-290.

Lin, T.-P., Matzarakis, A. & Hwang, R.-L., 2010. Shading effect on long-term outdoor thermal comfort. *Building and Environment,* 45(1), pp. 213-221.

Littlefair, P., 2001. Daylight, sunlight and solar gain in the urban environment. *Solar Energy,* 70(3), pp. 177-185.

Littlefair, P., 2011. Site layout planning for daylight and sunlight: A guide to good practice, second edition. IHS BRE Press, UK.

Liu, C., 2017. Details for thermal modelling of typical UK dwellings. *Data in Brief*.

Liu, C. & Coley, D., 2015a. Overheating Risk of UK Dwellings Under a Changing Climate. *Energy Procedia*, 78, pp. 2796-2801.

Liu, C. & Coley, D., 2015b. Spatial variations in overheating risk of dwellings under a changing climate: a case study of Sheffield, UK.

Liu, C., Kershaw, T., Eames, M.E. & Coley, D.A., 2016. Future probabilistic hot summer years for overheating risk assessments. *Building and Environment,* 105, pp. 56-68.

Liu, C., Kershaw, T., Fosas, D., Ramallo Gonzalez, A.P., Natarajan, S. & Coley, D.A., 2017. High resolution mapping of overheating and mortality risk. *Building and Environment,* 122, pp. 1-14.

Lomas, K.J. & Kane, T., 2013. Summertime temperatures and thermal comfort in UK homes. *Building Research & Information,* 41(3), pp. 259-280.

Matzarakis, A. & Mayer, H., 1996. Another Kind of Environmental Stress: Thermal Stress. Dessau-Roßlau: WHO - Collaborating centre for air quality management and air pollution control.

Matzarakis, A., Mayer, H. & Iziomon, M.G., 1999. Applications of a universal thermal index: physiological equivalent temperature. *International journal of biometeorology,* 43(2), pp. 76-84.

Matzarakis, A., Rutz, F. & Mayer, H., 2007. Modelling radiation fluxes in simple and complex environments—application of the RayMan model. *International journal of biometeorology,* 51(4), pp. 323-334.

Mavrogianni, A., Taylor, J., Davies, M., Thoua, C. & Kolm-Murray, J., 2015. Urban social housing resilience to excess summer heat. *Building Research & Information,* 43(3), pp. 316-333.

Mavrogianni, A., Wilkinson, P., Davies, M., Biddulph, P. & Oikonomou, E., 2012. Building characteristics as determinants of propensity to high indoor summer temperatures in London dwellings. *Building and Environment,* 55(0), pp. 117-130.

Mayer, H. & Höppe, P., 1987. Thermal comfort of man in different urban environments. *Theoretical and Applied Climatology,* 38(1), pp. 43-49.

McLeod, R.S., Hopfe, C.J. & Kwan, A., 2013. An investigation into future performance and overheating risks in Passivhaus dwellings. *Building and Environment,* 70, pp. 189-209.

Mulville, M. & Stravoravdis, S., 2016. The impact of regulations on overheating risk in dwellings. *Building Research & Information,* 44(5-6), pp. 520-534.

Murphy, J., 2000. Predictions of climate change over Europe using statistical and dynamical downscaling techniques. *International Journal of Climatology,* 20(5), pp. 489-501.

Murphy, J., Sexton, D., Jenkins, G., Boorman, P., Booth, B., Brown, K., Clark, R., Collins, M., Harris, G. & Kendon, L., 2010. *UK Climate Projections science report: Climate change projections.* Met Office Hadley Centre.

Mylona, A., 2012. The use of UKCP09 to produce weather files for building simulation. *Building Services Engineering Research and Technology,* 33, p. 13.

Narowski, P., Janicki, M. & Heim, D., 2013. Comparison of Untypical Meteorological Years (UMY) and their influence on building energy performance simulations. *In Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association.* Chambery, France, pp. 1414-1421.

NEA, 1960. Small-Sample Techniques. *The National Education Association Bulletin,* 38, p. 99.

Nicol, J.F., Hacker, J., Spires, B. & Davies, H., 2009. Suggestion for new approach to overheating diagnostics. *Building Research & Information,* 37(4), pp. 348-357.

Nicol, J.F. & Humphreys, M.A., 2002. Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy and Buildings,* 34(6), pp. 563-572.

Nikolopoulou, M., Baker, N. & Steemers, K., 2001. Thermal comfort in outdoor urban spaces: understanding the human parameter. *Solar Energy,* 70(3), pp. 227-235.

ODPM, 2006. Housing Health and Safety Rating System: Operating guidance. Office of the Deputy Prime Minister, London, UK.

Oikonomou, E., Davies, M., Mavrogianni, A., Biddulph, P., Wilkinson, P. & Kolokotroni, M., 2012. Modelling the relative importance of the urban heat island and the thermal quality of dwellings for overheating in London. *Building and Environment,* 57(0), pp. 223-238.

ONS, 2011a. *2011 Census Ward Profile No.4 – Housing and Accommodation.* Office for National Statistics, UK.

ONS, 2011b. Neighbourhood Statistics. In: Office for National Statistics, ed. London, UK.

Patidar, S., Jenkins, D.P., Gibson, G.J. & Banfill, P.F.G., 2011. Statistical techniques to emulate dynamic building simulations for overheating analyses in future probabilistic climates. *Journal of Building Performance Simulation,* 4(3), pp. 271-284.

Peacock, A.D., Jenkins, D.P. & Kane, D., 2010. Investigating the potential of overheating in UK dwellings as a consequence of extant climate change. *Energy Policy,* 38(7), pp. 3277-3288.

Perez, R., 1990. Modelling daylight availability and irradiance components from direct and global irradiance. *Solar Energy,* 44(5), p. 19.

Perry, M. & Hollis, D., 2005. The generation of monthly gridded datasets for a range of climatic variables over the UK. *International Journal of Climatology,* 25(8), pp. 1041-1054.

PHI, 2016. Criteria for the Passive House, EnerPhi and PHI Low Energy Building Standard. Darmstadt, Germany: Passive House Institute.

PHI, 2017. *designPH 1.1.60* [Online]. Passive House Institute, Germany. [Accessed 14/03 2017].

Pickup, J. & de Dear, R., Year. An outdoor thermal comfort index (OUT_SET*)-part I-the model and its assumptions. In: Biometeorology and urban climatology at the turn of the millenium. Selected Papers from the Conference ICB-ICUC, 2000. pp. 279-283.

Porritt, S., Shao, L., Cropper, P.C. & Goodier, C.I., 2010. Building orientation and occupancy patterns and their effect on interventions to reduce overheating in dwellings during heat waves. *IESD PhD Conference: Energy and Sustainable Development.* Institute of Energy and Sustainable Development, Queens Building, De Montfort University, Leicester, UK.

Porritt, S.M., 2012. *Adapting UK Dwellings for Heat Waves.* Doctor of Philosophy Thesis, De Montfort University.

Porritt, S.M., Cropper, P.C., Shao, L. & Goodier, C.I., 2012. Ranking of interventions to reduce dwelling overheating during heat waves. *Energy and Buildings,* 55(0), pp. 16-27.

Porson, A., Clark, P.A., Harman, I.N., Best, M.J. & Belcher, S.E., 2010. Implementation of a new urban energy budget scheme in the MetUM. Part I: Description and idealized simulations. *Quarterly Journal of the Royal Meteorological Society,* 136(651), pp. 1514-1529.

Portier CJ, Thigpen Tart K, Carter SR, Dilworth CH, Grambsch AE, Gohlke J, Hess J, Howard SN, Luber G, Lutz JT, Maslak T, Prudent N, Radtke M, Rosenthal JP, Rowles T, Sandifer PA, Scheraga J, Schramm PJ, Strickman D, Trtanj JM & P-Y, W., 2010. *A Human Health Perspective On Climate Change: A Report Outlining the Research Needs on the Human Health Effects of Climate Change.* Research Triangle Park, North Carolina, USA.

Ramallo-González, A.P., Vellei, M., Brown, M., Coley, D., 2015. A remote window surveying tool for energy efficient refurbishment. *6th International building Physics Conference.* Turin, Italy.

Randall, D.A., R.A. Wood, S. Bony, R. Colman, T. Fichefet, J. Fyfe, V. Kattsov, A. Pitman, J. Shukla, J. Srinivasan, R.J. Stouffer, A. Sumi and K.E. Taylor, 2007. Cilmate Models and Their Evaluation. *In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M.Tignor and H.L. Miller (eds.)].* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Richardson, I. & Thomson, M., 2010. Domestic electricity demand model. Centre for Renewable Energy Systems Technology, Department of Electronic and Electrical Engineering, Loughborough University, Leicestershire LE11 3TU, UK.

Robinson, D. & Haldi, F., 2008. Model to predict overheating risk based on an electrical capacitor analogy. *Energy and Buildings,* 40(7), pp. 1240-1245.

Smith, S.T. & Hanby, V., 2012. Methodologies for the generation of design summer years for building energy simulation using UKCP09 probabilistic climate projections. *Building Services Engineering Research and Technology,* 33(1), pp. 9-17.

Spagnolo, J. & de Dear, R., 2003. A field study of thermal comfort in outdoor and semi-outdoor environments in subtropical Sydney Australia. *Building and Environment,* 38(5), pp. 721-738.

Stoffel, T.L. & Rymes, M.D., 1998. Production of the weather year for energy calculations version 2 (WYEC2) data files/Discussion. *ASHRAE Transactions,* 104, p. 487.

Stott, P.A., Stone, D.A. & Allen, M.R., 2004. Human contribution to the European heatwave of 2003. *Nature,* 432(7017), pp. 610-614.

Taylor, J., Davies, M., Mavrogianni, A., Chalabi, Z., Biddulph, P., Oikonomou, E., Das, P. & Jones, B., 2014. The relative importance of input weather data for indoor overheating risk assessment in dwellings. *Building and Environment,* 76(0), pp. 81-91.

Taylor, J., Davies, M., Mavrogianni, A., Shrubsole, C., Hamilton, I., Das, P., Jones, B., Oikonomou, E. & Biddulph, P., 2016. Mapping indoor overheating and air pollution risk modification across Great Britain: A modelling study. *Building and Environment,* 99, pp. 1-12.

Taylor, J., Wilkinson, P., Davies, M., Armstrong, B., Chalabi, Z., Mavrogianni, A., Symonds, P., Oikonomou, E. & Bohnenstengel, S.I., 2015. Mapping the effects of urban heat island, housing, and age on excess heat-related mortality in London. *Urban Climate,* 14, Part 4, pp. 517-528.

The Research Advisors, 2006. *Required Sample Size* [Online]. Available from: http://research-advisors.com/tools/SampleSize.htm [Accessed 6 July 2016].

Thevenard, D.J. & Brunger, A.P., 2002. The development of typical weather years for international locations: part I, algorithms. *ASHRAE Transactions,* 108, p. 376.

Thorsson, S., Lindqvist, M. & Lindqvist, S., 2004. Thermal bioclimatic conditions and patterns of behaviour in an urban park in Göteborg, Sweden. *International journal of biometeorology,* 48(3), pp. 149-156.

Tian, W. & de Wilde, P., 2011. Thermal building simulation using the UKCP09 probabilistic climate projections. *Journal of Building Performance Simulation,* 4(2), pp. 105-124.

Tillson, A.-A., Oreszczyn, T. & Palmer, J., 2013. Assessing impacts of summertime overheating: some adaptation strategies. *Building Research & Information,* 41(6), pp. 652-661.

U.S. DOE, *EnergyPlus Weather Data* [Online]. U.S. Department of Energy. Available from: https://energyplus.net/weather [Accessed 18/04 2017].

UKCP09 UI, 2009. *UK Climate Projections User Interface* [Online]. The Environment Agency in partnership with the Met Office, UK. Available from: http://ukclimateprojections-ui.metoffice.gov.uk/ui/admin/login.php [Accessed 13/02 2016].

UN, 1992. *United Nation Framework Convention on Climate Change.* United Nations.

UNFCCC, 2015. Adoption of the Paris agreement—Proposal by the President—Draft decision -/CP.21. *2015 Paris Climate Conference.* Paris.

United Nations, 1992. *United Nations Framework Convention on Climate Change.* United Nations.

URBED, 2015. *Sheffield Garden City? Options for long term urban growth.* Urbanism, Environment and Design, UK.

Vandentorren, S., Bretin, P., Zeghnoun, A., Mandereau-Bruno, L., Croisier, A., Cochet, C., Riberon, J., Siberan, I., Declercq, B. & Ledrans, M., 2006. August 2003 heat wave in France: risk factors for death of elderly people living at home. *European journal of public health*, 16(6), pp. 583-91.

VDI, 1998. Methods for the human-biometeorological assessment of climate and air hygiene for urban and regional planning. Part I: climate. VDI guideline 3787. Part 2. . Beuth, Berlin.

Vernon, H. & Warner, C., 1932. The influence of the humidity of the air on capacity for work at high temperatures. *Journal of Hygiene*, 32(03), pp. 431-462.

Watkins, R., Levermore, G. & Parkinson, J., 2011. Constructing a future weather file for use in building simulation using UKCP09 projections. *Building Services Engineering Research and Technology*, 32(3), pp. 293-299.

Watkins, R., Levermore, G. & Parkinson, J., 2012. The design reference year - a new approach to testing a building in more extreme weather using UKCP09 projections. *Building Services Engineering Research and Technology,* 34(2), pp. 165-176.

Winslow, C.E.A., Herrington, L.P. & Gagge, A.P., 1937. Physiological reactions and sensations of pleasantness under varying atmospheric conditions. Trans ASHVE pp. 179–196.

Wright, A., Young, A. & Natarajan, S., 2005. Dwelling temperatures and comfort during the August 2003 heat wave. *Building Services Engineering Research and Technology*, 26(4), pp. 285-300.

Yaglou, C. & Minaed, D., 1957. Control of heat casualties at military training centers. *Arch. Indust. Health*, 16(4), pp. 302-16.

Appendix A

Dwelling geometry, floor plan and 3D view of five UK dwelling types

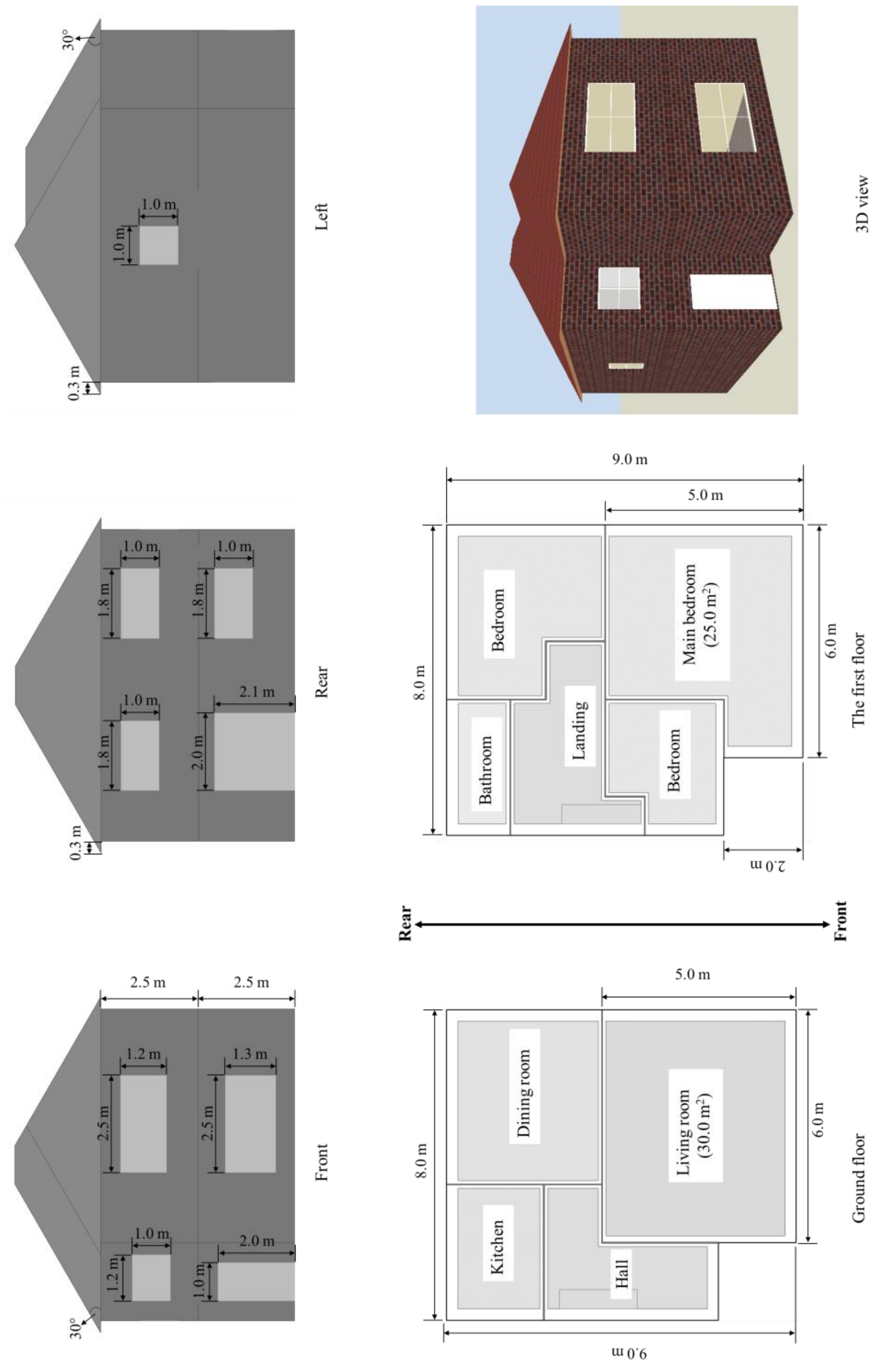


Figure A-1. Geometry of the typical detached house

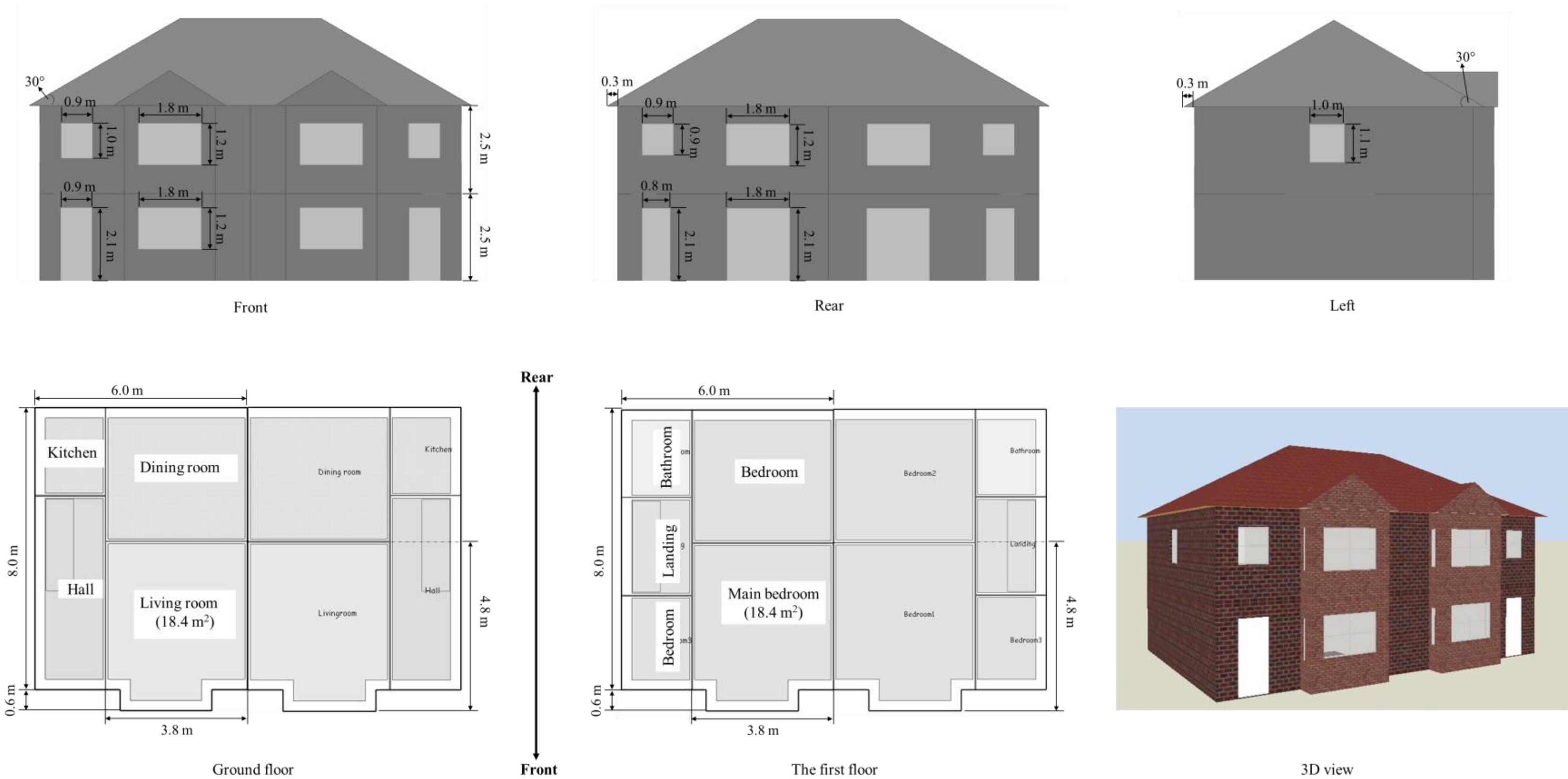


Figure A-2. Geometry of the typical semi-detached house

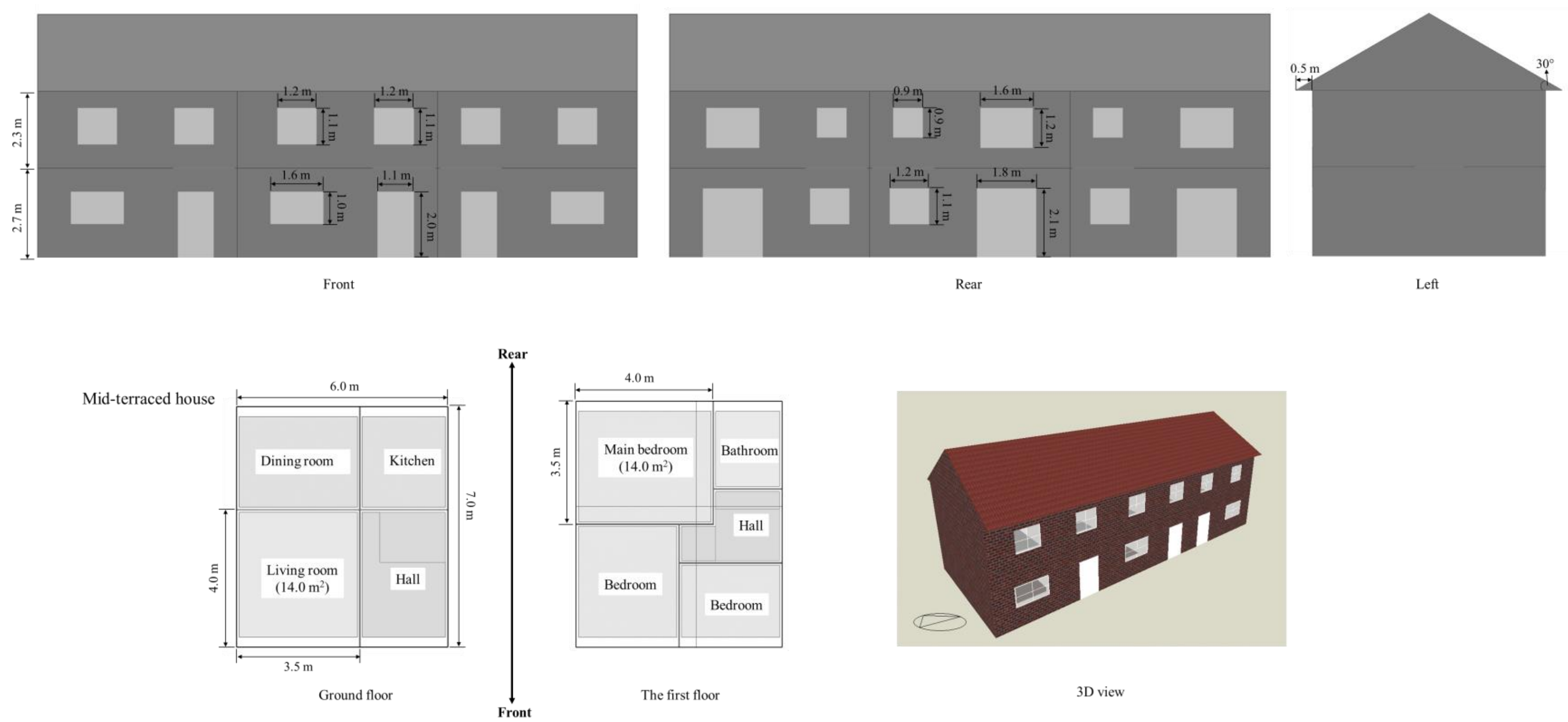


Figure A-3. Geometry of the typical terraced house

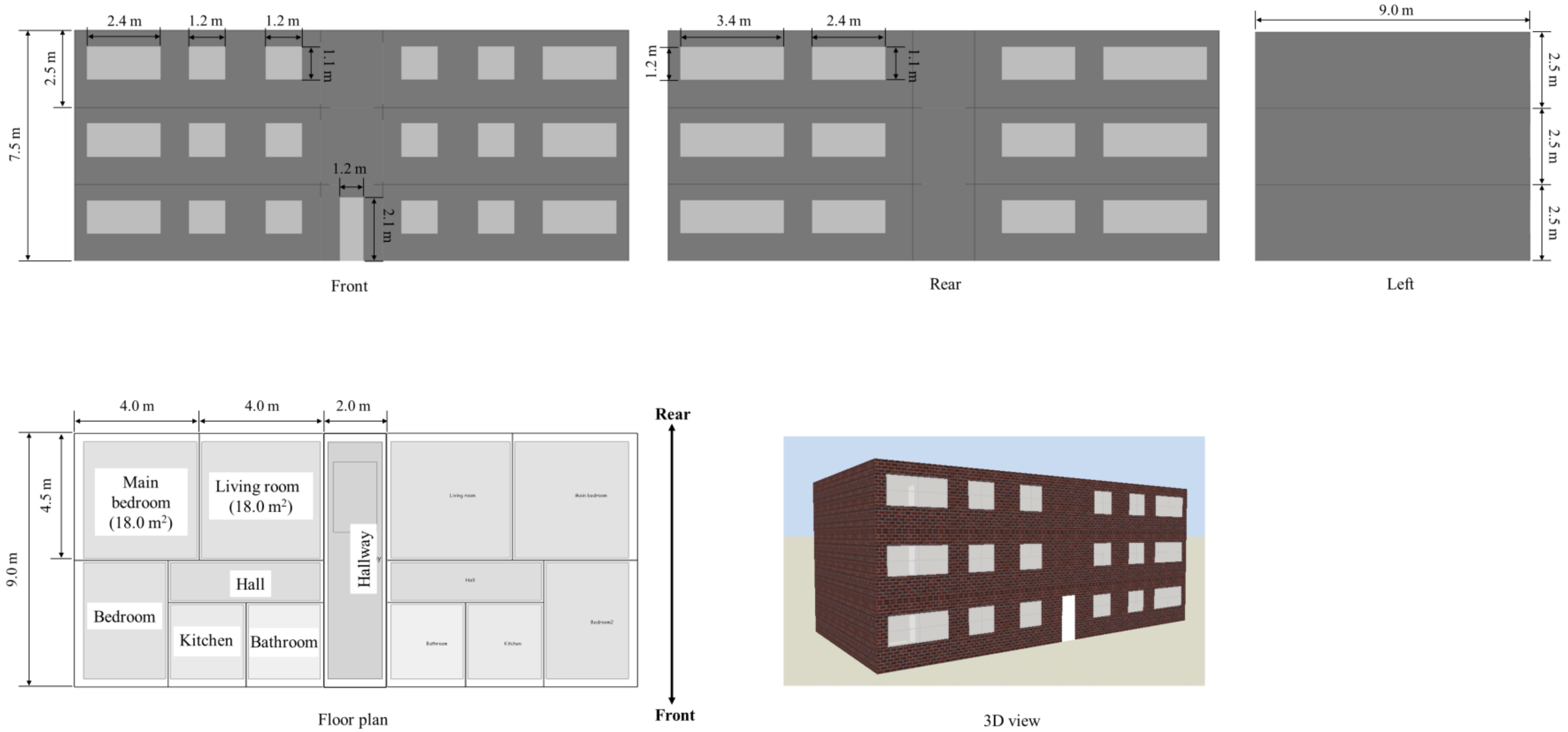


Figure A-4. Geometry of the typical flat

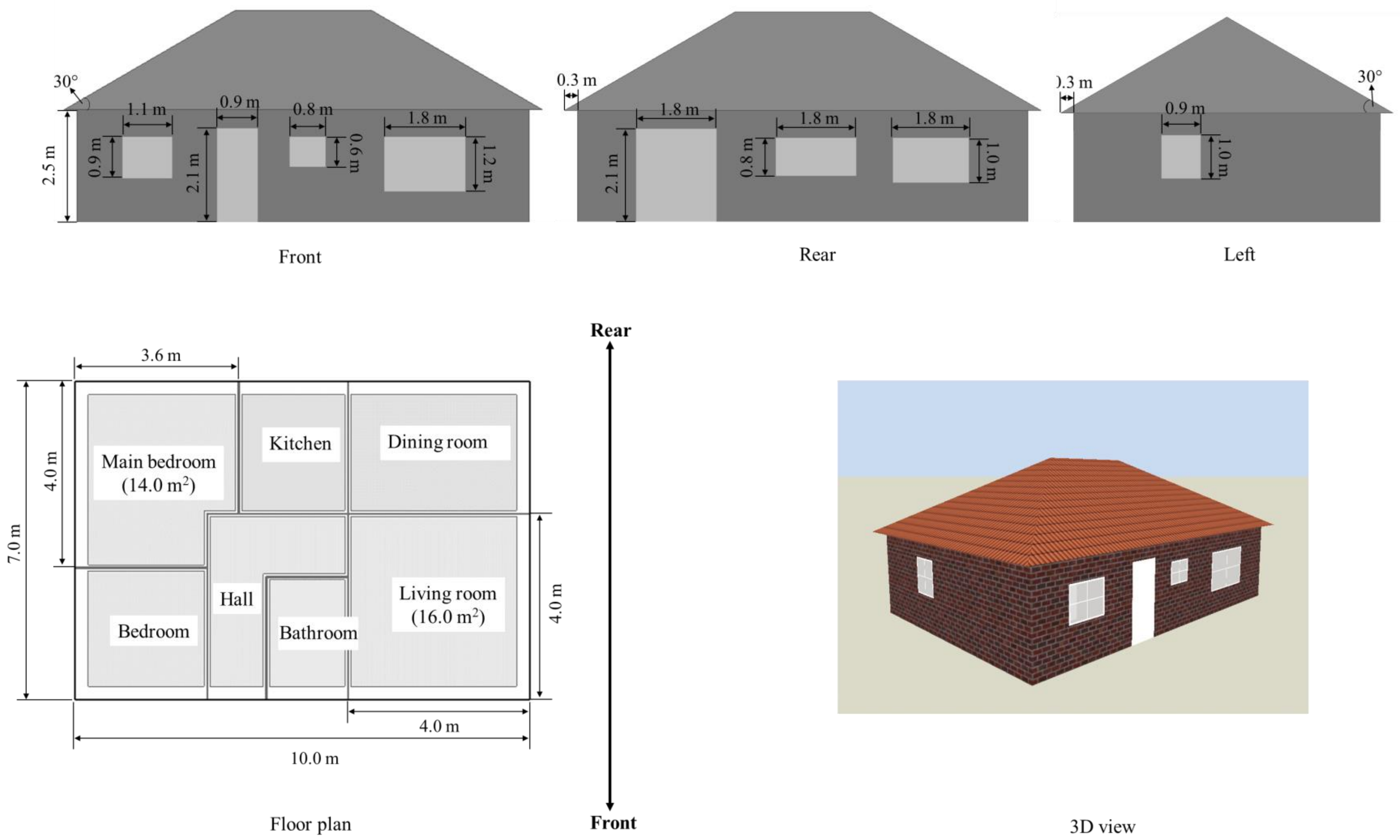


Figure A-5. Geometry of the typical bungalow

Dwelling construction details

Table A-1. Construction details and U-values

		Construction	U-value (W/m^{2}K)
External wall	Uninsulated solid wall	220 mm brickwork outer leaf 13 mm plaster (dense)	2.09
	Uninsulated cavity wall	105 mm brickwork outer leaf 150 mm air layer (Air gap>25mm) 105 mm brick, inner leaf 13 mm plaster (dense)	1.44
	Insulated cavity wall	105 mm brickwork outer leaf 100 mm air layer (Air gap>25mm) 50 mm EPS Expanded Polystyrene (Standard) 105 mm brick, inner leaf 13 mm plaster (dense)	0.5
Internal partition	Heavyweight	13 mm plaster (lightweight) 105 mm brick, inner leaf 13 mm plaster (lightweight)	1.69
	Lightweight	15 mm gypsum plasterboard 50 mm air layer 15 mm gypsum plasterboard	1.79
Party wall		13 mm plaster (dense) 215 mm brick, inner leaf 13 mm plaster (dense)	1.45
Internal floor		10 mm plasterboard (ceiling) 200 mm air layer 20 mm timber flooring 5 mm carpet/textile flooring	1.33
Ground floor	Uninsulated	750 mm clay underfloor 25 mm brick slips 100 mm cast concrete 50 mm flooring screed	1.1
	Insulated	500 mm clay underfloor 50 mm EPS Expanded Polystyrene 150 mm concrete roof/floor slab 50 mm flooring screed	0.50

Table A-2. Construction details and U-values- continued

		Construction	U-value (W/m²K)
Roof	Uninsulated flat roof	25 mm stone chippings for roof 75 mm roof screed 150 mm cast concrete 10 mm air layer 13 mm plaster (dense)	1.6
	Insulated flat roof	25 mm stone chippings for roof 19 mm Asphalt 50 mm Extruded polystyrene 10 mm Polythene 150 mm concrete roof/floor slab 13 mm plaster (dense)	0.46
	Uninsulated pitched roof	13 mm slate 1000 mm cold loft space 9.5 mm plasterboard (ceiling)	2.0
	Insulated pitched roof	10 mm concrete roof tiles 1000 mm cold loft space 250 mm min wool quilt 9.5 mm plasterboard (ceiling)	0.16
Doors		35 mm painted oak	2.25

Table A-3. Window characteristics

		constructions	U-value (W/m²K)	SHGC
Glazing	Single	6 mm generic clear glass	5.80	0.83
	Double	6 mm generic clear glass 13 mm air 6 mm generic clear glass	2.71	0.70
Window frames	Wooden	20 mm oak	3.63	-
	uPVC	20 mm polyvinylchloride	3.48	-

Table A-4. Properties of construction materials

material	Density (kg/m^3)	Thermal conductivity (W/m·K)	Specific heat capacity (J/kg·K)
Brick (outer)	1700	0.77	840
Brick (inner)	1700	0.56	850
Brick slips	1700	0.77	1000
Slate	1602	1.00	1464
Cast concrete	2000	1.35	1000
concrete roof tiles	2100	1.50	1000
Concrete roof/floor slab	2000	1.35	1000
plaster (lightweight)	600	0.18	1000
Plaster (dense)	1300	0.57	1000
Plasterboard	950	0.16	840
plasterboard (ceiling)	900	0.21	1000
Gypsum plasterboard	900	0.25	1000
Asphalt	2100	0.7	1000
Polythene	500	0.25	1000
EPS Expanded Polystyrene (standard)	15	0.04	1400
Extruded polystyrene	40	0.027	1300
Min wool quilt	12	0.04	1030
Carpet/textile flooring	200	0.06	1300
Timber flooring	650	0.14	1200
Flooring screed	1200	0.41	1000
Painted oak	700	0.19	2390
polyvinylchloride	1390	0.17	900

Appendix B

<table>
<tr><td colspan="10">This declaration concerns the article entitled:</td></tr>
<tr><td colspan="10">Future probabilistic hot summer years for overheating risk assessments</td></tr>
<tr><td colspan="10">Publication status (tick one)</td></tr>
<tr><td>Draft manuscript</td><td></td><td>Submitted</td><td></td><td>In review</td><td></td><td>Accepted</td><td></td><td>Published</td><td>√</td></tr>
<tr><td>Publication details (reference)</td><td colspan="9">Liu, C., Kershaw, T., Eames, M.E. and Coley, D.A., 2016. Future probabilistic hot summer years for overheating risk assessments. Building and Environment, 105, pp. 56-68.
http://dx.doi.org/10.1016/j.buildenv.2016.05.028</td></tr>
<tr><td>Candidate's contribution to the paper (detailed and also given as a percentage).</td><td colspan="9">The candidate contributed to/ considerably contributed to/ predominantly executed the …

Formulation of ideas: 85%
I presented the main idea of this work and discussed with my supervisor Prof David Coley who provided an advice on it.

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I designed an innovative and viable methods to achieve the research aims. The co-authors shared their expertise with me.

Experimental work: 100%
I produced all of the dataset, i.e. different types of future weather years used in this work.

Presentation of data in journal format: 80%
I wrote the first draft of this academic paper. My co-authors reviewed the paper and gave critical and insightful comments. The English throughout the paper was improved by Dr Tristan Kershaw.</td></tr>
<tr><td>Statement from candidate</td><td colspan="9">This paper reports on original research I conducted during the period of my Higher Degree by Research candidate.</td></tr>
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Appendix C

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Publication: Building and Environment
Publisher: Elsevier
Date: 15 August 2016

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<tr><td>Publication details (reference)</td><td colspan="9">Liu, C., Kershaw, T., Fosas, D., Ramallo Gonzalez, A.P., Natarajan, S. and Coley, D., 2017. High resolution mapping of overheating and mortality risk. Building and Environment, 112, pp. 1-14.
https://doi.org/10.1016/j.buildenv.2017.05.028</td></tr>
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I presented the main idea of this work and discussed with my supervisor Prof David Coley who provided an advice on it.

Design of methodology: 90%
I designed an innovative and viable methods to achieve the research aims. The co-authors shared their expertise with me.

Experimental work: 95%
I produced all of the dataset, i.e. different types of future weather years used in this work. Co-authors assisted me to run thousands of dynamic thermal simulations on the High Performing Computing system at University of Bath.

Presentation of data in journal format: 80%
I wrote the first draft of this academic paper. My co-authors reviewed the paper and gave critical and insightful comments. The English throughout the paper was improved by Dr Tristan Kershaw.</td></tr>
<tr><td>Statement from candidate</td><td colspan="9">This paper reports on original research I conducted during the period of my Higher Degree by Research candidate.</td></tr>
<tr><td>Signed</td><td colspan="6">Chunde Liu</td><td>Date</td><td colspan="2">03/07/2017</td></tr>
</table>

Appendix E

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Title: High resolution mapping of overheating and mortality risk
Author: C. Liu,T. Kershaw,D. Fosas,A.P. Ramallo Gonzalez,S. Natarajan,D.A. Coley
Publication: Building and Environment
Publisher: Elsevier
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